Welcome to Project Seven

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Welcome paragraph...

P7 Chapter 1 - The Human Data digital Toolkit (HDDT)

Thesis Chapter 6 Sections 6.16 and 6.17

File name: jnb_hddt_intro

1.1 Links to chapter sections

Jump to:
My PhD project
HDDT Objective
Datasets
Data Pipeline
SQLite Database
Architecture
Big Data

1.2 The data and model objectives

The data:

My own research, in collaboration with others, has revealed the extensive social connectivity between the roughly 3000 members of a 'Quaker Led Group (QLG). The QLG's activities are spread across five organisations in Britain active between 1830 and 1870, which the Quaker members helped to set up and staff. I call these five organisations, the 'Centres for the Emergence of Discipline of Anthropology in Britain' (CEDA).Amongst the 3000 members of the CEDA are approximatley 600 Quakers, approximately 20% of the membership.

The CEDA comprises:

- The Quaker Committee on the Aborigines, QCA - (1831 – 1846)
- The Aborigines Protection Society, APS - (1837 – 1848)
- The Ethnological Society of London, ESL - (1843 – 1848)

- The Anthropological Society of London, ASL - (1861 – 1869)
- The Anthropological Institute, AI – (1871). A merger of the ESL and ASL.

The HDDT requirements

- Able to handle the data (quantity and quality)
- User interventions
- Open source
- In common use
- Ease of Interoperability
- Free online learning aids
- Supported by University of Birmingham
- Independent Research Group friendly

The model:

I have designed, built a suite of open-source relational database technologies and digital analytic tools to visualise and scrutinise the entire CEDA community over the 40 years of their collective action from their beginnings up to the formation of the Royal Anthropological Institute (1830-1870). I have identified the Quakers amongst them so that the community can be explored at both whole group and Quaker members levels. I am able to model the prosopographical relationships between the individual members of the CEDA both statically and dynamically (through time). I can analyse bipartite relationships for common attributes: kinship (Quakers only), education, occupations, locations and organisations.I have buit a Human Data Digital Toolkit (HDDT)to collect, clean, manage and present the data. The model and data have been designed to answer three questions:

Question 1:

Can the model reveal the connectivity between the CEDA memberships and the four organisations that began with a concern for the plight of aborigines and led to the establishment of the discipline of anthropology in Britain 1830 - 1870? This question is important because it resolves current uncertainty over the origins of the discipline of anthropology in Britain and the extent of Quaker involvement.

Question 2

Can the model seamlesssly facilitate an examination of Quaker to Quaker relationships, Quaker roles in the CEDA at the individual and at the individual society and whole group levels?

Question 3

Can the model reveal the key networking role played by the Quaker Thomas Hodgkin MD (1798 – 1866) from the beginnings of the CEDA in 1830 and up to his death in 1866?

To create containers for the data collected in csv sheets from several sources and in different arrangements. To facilitate data combining and cleaning. To establish an auditable data pipeline. To hold the data in an sql database. The model data can then be analysed and visualised by using Gephi which is a compatible open source software package. The HDDT is designed to enable human prosopographical ordered data to be surveyed, much as an archaeologist might use a variety of technologies to survey a territorial site of historical interest.

The HDDT is a new approach to the Digital Humanities. (1) in is exclusive concentrtion on Evidence Basded Prosopographical data using open source data science techniques readily available to the lone researcher and capable of execution on an average desktop computer. The objective is to facilitate the study large sets of prosopographical data (of variable quality and quantity) either as individuals or groups of persons and embedded sub-groups of persons.

Exponential population growth in the nineteenth century combined with a cultural, disciplined and extensive interest in collecting, cataloguing and preserving historial artefacts and manuscripts, offers to the researcher an opportunity to study individuals, communities and whole sections of societies en masse.

The archives of the nineteenth century are often very large, too big to be surveyed only by the naked eye. (and are immense when viewed collectively). From a prosopographical point of view they offer a rich source of prosopographical data, often organised as metadata (catalogued and frequently cross-referenced, if poorly referenced to primary sources).

The HDDT facilitates the study of prosopographical data in itself, it is purposely free of narratology and interpretation. It, and other tools like it are essentil to all researchers wishing to underdand the

peoples of the past and their relationships.

1.3 HTTD technical Objective

Archival data can now be surveyed much as an archaeological site can - by using technology

1.4 Contributing datasets

The HDDT integrates ordered datasets from a variety of sources to create one SQLite HTTD database

Historians can create a bespoke database taking data from multiple sources using the HDDT. This project takes data from:

Source	Records
Royal Anthropological Insitiute (RAI)	2260
Quaker Family History Society (QFHS)	593
Independent research at RAI	1171
Independent research at Friends House Quaker Archive, London	30
total records	3095

1.5 Dataset variability

Component datasets can be ‘Complete’, ‘Incomplete’ or ‘Irregular’ as long as the contributing datasets consist of records where at least one column is shared. In this Project person_name was common to all datasets.

A ‘complete’ dataset

Would be one like this, where all of the data is contained witin a perfect rectangular block of cells (‘containers’) and every container contains only one data item and every data item can be located by the coordinates ‘Row n, Column n’

An ‘incomplete’ dataset

When historical data is used often some data is missing (it can be permanently lost). The HDDT is able to accept ‘Incomplete’ datasets. The HDDT does not lose functionality because of the incomplete nature of much historical data.

An ‘irregular’ dataset

The HDDT has been designed to accept Irregular datasets. The surviving evidence of past lives is not only often Incomplete, it is frequently Irregular. An additional complication arsises when data from multiple sourcesmust be combined into a single dataset. Here it is likely that multiple donor datasets will have have different dimensions. This arises because either the data in itself is intrinsically different or because different data collectors have compiled data at different times and to different standards or simply prefer different collecting methods.

For the HDDT a qualifying contributing dataset is a data set of any dimensions, complete, incomplete or irregular. The only requirement is that all contributing datasets must consist of

prosopographical data and with the key field as PERSON-NAME.

1.6 Data pipeline

In the HDDT data transits through a data pipeline with each component of the pipeline managed by a different technology. Great care was taken to ensure the the technological array comprised of open source technologies, fully integratable (losslessly) and widely supported and in wide use in the academic community.

1.7 Model output - Data visualisation criteria

In order to answer the three questions set the selected visualisation technology needed to be able to produce an affiliation network for social network analysis (a bipartite graph). Additionally it needed to be able to present data statically, where all 40 years data are compressed into one visualisation. This would enable the full extent of the network examined to be seen as a single image. Additionally, because the network evolves and changes over time, it was desirable that the technology handle dynamic data, where the network can be visualised progressively one year at a time from 1830 to 1870. Gephi met the project criteria.

1.8 Integrated HTTD SQLite database - 3095 persons

Entity Relationship Diagram (ERD)

At the heart of the HDDT (and the SQLite database) is the ‘person table’, this holds the data (attributes) unique to each person. All contributing datasets have one or more columns containing person names. Further columns often contain attribut data. Some attribute data may be recorded in sevearl donor datasets. Conflicts between dataset Person Name’s are resolved by first choosing to accept the ‘RAI dataset’ as the ‘Authority Index’. Matching names across donor datasets was done

by hand in the CSV sheets. This is because (1) person name records from datasets other then the deemed (RAI) dataset were small in number, (2) because name matching requires judgement (names ofthen repeat in familiies and their might be little attributive data in common between the other donor data set and the RAI dataset and (3) because human matching is common practise in genealogy systems, even if algorithms are used to find possible matches. The finding of possible matches in this project was performed most efficiently by the human eye. (A move to the digital should not needlessly repalce the human).

Tables of data items shared amongst persons (such as ‘occupation’, ‘location’, ‘societies’, ‘clubs’) are linked to the person table by m2m tables.

There are also person_person tables to capture family relationships

1.9 HDDT Design Architecture

The following packages are required to make the HDDT:

package	Use
GitHub	for version control and sharing
SQL	the database
VSC	building the database
VSC	version control interface to Git
DBeaver	data cleaning, data management and ananysis
Jupyter Notebook	data analysis
Gephi	data visualisation

They were chosen because they are universal, popular, open-source and suitable for handling historical ordered data.

1.10 Project containers contain all required resources

Data management needs caeful consideration and design. The HDDT uses the cocept of project containers where every container is set up and initialised as a GitHub repo. Then a Jupyter Notebook is created in the same container. All resources needed for a project are then copied from master containers (such as the template CSV files and dataframes in the ceda/database/views container.

Gexf graph files and gexf project files also are set up and saved in each container.

Relative links can then be used and their integrity preserved.

GitGub can also be used for version control providing an audit trail of changes, additions and deletions to the HDDT container system.

1.11 Github

The entire HDDT project, its description, structure, organisation and resources are contained in one GitHub account:

KelvinBeerJones

1.12 SQLite recommendations

SQLite is a C-language library that implements a small, fast, self-contained, high-reliability, full-featured, SQL database engine. SQLite is the most used database engine in the world. SQLite is built into all mobile phones and most computers and comes bundled inside countless other applications that people use every day (https://www.sqlite.org/index.html).

SQLite is a C-language library that implements a small, fast, self-contained, high-reliability, full-featured, SQL database engine. SQLite is the most used database engine in the world. SQLite is built into all mobile phones and most computers and comes bundled inside countless other applications that people use every day. The SQLite file format is stable, cross-platform, and backwards compatible and the developers pledge to keep it that way through the year 2050. SQLite database files are commonly used as containers to transfer rich content between systems and as a long-term archival format for data. There are over 1 trillion SQLite databases in active use. SQLite source code is in the public-domain and is free to everyone to use for any purpose. https://www.sqlite.org/about.html

In the two decades following its initial release, SQLite has become the most widely deployed database engine in existence. Today, SQLite is found in nearly every smartphone, computer, web browser, television, and automobile. Several factors are likely responsible for its ubiquity, including its in-process design, standalone codebase, extensive test suite, and cross-platform file format. While it supports complex analytical queries, SQLite is primarily designed for fast online transaction processing (OLTP), employing row-oriented execution and a B-tree storage format. However, fueled by the rise of edge computing and data science, there is a growing need for efficient in-process online analytical processing (OLAP). DuckDB, a database engine nicknamed “the SQLite for analytics”, has recently emerged to meet this demand. While DuckDB has shown strong performance on OLAP benchmarks, it is unclear how SQLite compares. Furthermore, we are aware of no work that attempts to identify root causes for SQLite’s performance behavior on OLAP workloads. In this paper, we discuss SQLite in the context of this changing workload landscape. We describe how SQLite evolved from its humble beginnings to the full-featured database engine it is today. We evaluate the performance of modern SQLite on three benchmarks, each representing a different flavor of in-process data management, including transactional, analytical, and blob processing. We delve into analytical data processing on SQLite, identifying key bottlenecks and weighing potential solutions. As a result of our optimizations, SQLite is now up to 4.2X faster on SSB. Finally, we discuss the future of SQLite, envisioning how it will evolve to meet new demands and challenges. ‘Sqlite: past, present, and future’ Gaffney, Kevin P, Prammer, Martin Brasfield, Larry Hipp, D Richard Kennedy, Dan Patel, Jignesh M (Gaffney et al. 2022, 3535)

1.13 VSC recommendations

Visual Studio Code is a lightweight but powerful source code editor which runs on your desktop and is available for Windows, macOS and Linux. It comes with built-in support for JavaScript,

TypeScript and Node.js and has a rich ecosystem of extensions for other languages (such as C++, C#, Java, Python, PHP, Go) and runtimes (such as .NET and Unity)(https://code.visualstudio.com/).

‘Visual Studio Code, commonly referred to as VS Code,is an integrated development environment developed by Microsoft for Windows, Linux, macOS and web browsers. Features include support for debugging, syntax highlighting, intelligent code completion, snippets, code refactoring, and embedded version control with Git. Users can change the theme, keyboard shortcuts, preferences, and install extensions that add functionality. Visual Studio Code is proprietary software released under the “Microsoft Software License”, but based on the MIT licensed program named “Visual Studio Code — Open Source” (also known as “Code — OSS”), also created by Microsoft and available through GitHub. In the 2024 Stack Overflow Developer Survey, out of 58,121 responses, 73.6% of respondents reported using Visual Studio Code, more than twice the percentage of respondents who reported using its nearest text editor and/or IDE alternative, Visual Studio. https://en.wikipedia.org/wiki/Visual_Studio_Code

‘Microsoft develops the free code editor Visual Studio Code (VSCode), that is used by more than 11 million users. In the StackOverflow developer survey from 2019, about 50% of the participants stated that they use VSCode, showing how popular this editor has become. The underlying source code is considered free (as in free speech) and referred to as Code - OSS. Microsoft uses Code - OSS as a base, slightly modifies it (e.g. adds a marketplace integration for distributing plugins), and releases it with a proprietary license under the name \Visual Studio Code”. Although this custom license makes VSCode technically speaking non-free and non-open source, other distributions of Code - OSS are free and contain substitutes for the missing features, for example VSCodium. Further analysis of VSCode and Code - OSS regarding aspects of FOSS (free and open source software) development can be found in the extensive preliminary study that was conducted before the project phase.’ ‘ Practical Study of Visual Studio Code’ Michael Plainer (Plainer 2021, 2)

1.14 VSC (Version control interface local to online Git Repo’s

1.15 DBeaver recommendations

‘DBeaver is a universal database management tool for everyone who needs to work with data in a professional way. With DBeaver you are able to manipulate your data, for example, in a regular spreadsheet, create analytical reports based on records from different data storages, and export information in an appropriate format. For advanced database users, DBeaver suggests a powerful SQL-editor, plenty of administration features, abilities of data and schema migration, monitoring database connection sessions, and a lot more. Out-of-the box DBeaver supports more than 80 databases. Having usability as its main goal, DBeaver offers:

- Carefully designed and implemented User Interface
- Support of Cloud data sources
- Support for Enterprise security standard
- Capability to work with various extensions for integration with Excel, Git, and others.
- Great number of features
- Multiplatform support’ dbeaver/dbeaver

DBeaver is a SQL client software application and a database administration tool. For relational databases it uses the JDBC application programming interface (API) to interact with databases via a JDBC driver. For other databases (NoSQL) it uses proprietary database drivers. It provides an editor that supports code completion and syntax highlighting. It provides a plug-in architecture (based on the Eclipse plugins architecture) that allows users to modify much of the application’s behavior to provide database-specific functionality or features that are database-independent. It is written in Java and based on the Eclipse platform. The community edition (CE) of DBeaver is a free and open source software that is distributed under the Apache License. A closed-source enterprise edition of DBeaver is distributed under a commercial license. https://en.wikipedia.org/wiki/DBeaver

Universal Database Tool

DBeaver is a free multi-platform database tool for developers, database administrators, analysts and all people who need to work with databases. Supports all popular databases: MySQL, PostgreSQL, SQLite, Oracle, DB2, SQL Server, Sybase, MS Access, Teradata, Firebird, Apache Hive, Phoenix, Presto, etc.(https://dbeaver.io/)

1.16 Jupyter Notebook recommendations

The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning. (https://jupyter.org/).

‘The Jupyter notebook is an open-source, browser-based tool functioning as a virtual lab notebook to support workflows, code, data, and visualizations detailing the research process. It is machine and human-readable, which facilitates interoperability and scholarly communication. These notebooks can live in online repositories and provide connections to research objects such as datasets, code, methods documents, workflows, and publications that reside elsewhere. Jupyter notebooks are one means to make science more open. Their relevance to the JCDL community lies in their interaction with multiple components of digital library infrastructure such as digital identifiers, persistence mechanisms, version control, datasets, documentation, software, and publications. Our poster examines how Jupyter notebooks embody the FAIR (Findable, Accessible, Interoperable, Reusable) principles for digital objects and assess their utility as viable tools for scholarly communication.’ ‘Using the Jupyter notebook as a tool for open science: An empirical study’ Randles Bernadette M, Pasquetto Irene V, Golshan Milena S, Borgman Christine L. (Randles et al. 2017, 1)

1.17 Gephi recommends

‘Gephi is an open source software for graph and network analysis. It uses a 3D render engine to display large networks in real-time and to speed up the exploration. A flexible and multi-task architecture brings new possibilities to work with complex data sets and produce valuable visual results. We present several key features of Gephi in the context of interactive exploration and interpretation of networks. It provides easy and broad access to network data and allows for spatializing, filtering, navigating, manipulating and clustering. Finally, by presenting dynamic features of Gephi, we highlight key aspects of dynamic network visualization.’ Bastian Mathieu, Heymann Sebastien, Jacomy, Mathieu Gephi: an open source software for exploring and manipulating networks. (Bastian, Heymann, and Jacomy 2009, 361)

Gephi is a tool for data analysts and scientists keen to explore and understand graphs. Like Photoshop™ but for graph data, the user interacts with the representation, manipulate the structures, shapes and colors to reveal hidden patterns. The goal is to help data analysts to make hypothesis, intuitively discover patterns, isolate structure singularities or faults during data sourcing. It is a complementary tool to traditional statistics, as visual thinking with interactive interfaces is now recognized to facilitate reasoning. This is a software for Exploratory Data Analysis, a paradigm appeared in the Visual Analytics field of research. https://gephi.org/features/

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1.18 Excel recommends

https://www.datacamp.com/tutorial/data-cleaning-in-excel-a-beginners-guide

https://cartong.pages.gitlab.cartong.org/learning-corner/en/3_nettoyage/3_3_nettoyage_donnees

1.19 References

Bastian, Mathieu, Sebastien Heymann, and Mathieu Jacomy. 2009. “Gephi: an open source software for exploring and manipulating networks.” Proceedings of the international AAAI conference on web and social media.

Gaffney, Kevin P, Martin Prammer, Larry Brasfield, D Richard Hipp, Dan Kennedy, and Jignesh M Patel. 2022. “Sqlite: past, present, and future.” Proceedings of the VLDB Endowment 15 (12).

Plainer, Michael. 2021. “Practical Study of Visual Studio Code.”

Randles, Bernadette M, Irene V Pasquetto, Milena S Golshan, and Christine L Borgman. 2017. “Using the Jupyter notebook as a tool for open science: An empirical study.” 2017 ACM/IEEE Joint Conference on Digital Libraries (JCDL).

1.20 600 Quakers amongst 3000 activists for 40 years.

P7 Chapter 2 The CEDA Members

Thesis Chapter 6 Section 6.6

File name: jnb_hddt_sql_tables

Install necessary resources

```
import pandas as pd

import csv

# First call the sql tables as they appear in the database (Part One)

ceda = pd.read_csv ('ceda_202107151833.csv')
club = pd.read_csv ('club_202107151833.csv')
location = pd.read_csv ('location_202107151833.csv')
person_ceda = pd.read_csv ('m2m_person_ceda_202107151835.csv')
person_club = pd.read_csv ('m2m_person_club_202107151835.csv')
person_location = pd.read_csv ('m2m_person_location_202107151835.csv')
person_occupation = pd.read_csv ('m2m_person_occupation_202107151836.csv')
person_person = pd.read_csv('m2m_person_person_202107151836.csv')
person_religion = pd.read_csv ('m2m_person_religion_202107151836.csv')
person_society = pd.read_csv ('m2m_person_society_202107151836.csv')
occupation = pd.read_csv ('occupation_202107151834.csv')
person = pd.read_csv ('person_202107151834.csv')
religion = pd.read_csv ('religion_202107151834.csv')
society = pd.read_csv('society_202107151834.csv')

# next call the sql tables rendered in Gephi format (Part Two)

# call all Names

gephi_all_names = pd.read_csv ('vw_2_all_bipartite_memberships_202107121854.csv')
gephi_names_notceda = pd.read_csv ('vw_2_all_bipartite_memberships_xceda_2021071218

# Then call all Tuples (Source and Target)

gephi_person_ceda = pd.read_csv ('vw_2_ceda_membership_202107121855.csv')
gephi_person_club = pd.read_csv ('vw_2_club_membership_202107121855.csv')
gephi_person_location = pd.read_csv ('vw_2_location_membership_202107121856.csv')
gephi_person_occupation = pd.read_csv ('vw_2_occupation_membership_202107121856.csv
gephi_person_person = pd.read_csv('vw_2_person_person_relationships_202107161545.cs
gephi_person_religion = pd.read_csv ('vw_2_religion_membership_202107121856.csv')
gephi_person_society = pd.read_csv ('vw_2_society_membership_202107121858.csv')

import matplotlib.pyplot as plt

plt.rcParams.update({'font.size': 18})

plt.rc('figure', figsize=(20, 10))

import numpy as np
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
Cell In[1], line 7
      3 import csv
      5 # First call the sql tables as they appear in the database (Part One)
----> 7 ceda = pd.read_csv ('ceda_202107151833.csv')
      8 club = pd.read_csv ('club_202107151833.csv')
      9 location = pd.read_csv ('location_202107151833.csv')

File /Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
   1013 kwds_defaults = _refine_defaults_read(
   1014     dialect,
   1015     delimiter,
   (...)
   1022     dtype_backend=dtype_backend,
   1023 )
   1024 kwds.update(kwds_defaults)
-> 1026 return _read(filepath_or_buffer, kwds)

File /Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
    617 _validate_names(kwds.get("names", None))
    619 # Create the parser.
--> 620 parser = TextFileReader(filepath_or_buffer, **kwds)
    622 if chunksize or iterator:
    623     return parser

File /Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
   1617     self.options["has_index_names"] = kwds["has_index_names"]
   1619 self.handles: IOHandles | None = None
-> 1620 self._engine = self._make_engine(f, self.engine)

File /Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
   1878     if "b" not in mode:
   1879         mode += "b"
-> 1880 self.handles = get_handle(
   1881     f,
   1882     mode,
   1883     encoding=self.options.get("encoding", None),
   1884     compression=self.options.get("compression", None),
   1885     memory_map=self.options.get("memory_map", False),
   1886     is_text=is_text,
   1887     errors=self.options.get("encoding_errors", "strict"),
   1888     storage_options=self.options.get("storage_options", None),
   1889 )
   1890 assert self.handles is not None
   1891 f = self.handles.handle

File /Library/Frameworks/Python.framework/Versions/3.10/lib/python3.10/site-packages
    868 elif isinstance(handle, str):
    869     # Check whether the filename is to be opened in binary mode.
    870     # Binary mode does not support 'encoding' and 'newline'.
    871     if ioargs.encoding and "b" not in ioargs.mode:
    872         # Encoding
```

```
--> 873         handle = open(
    874             handle,
    875             ioargs.mode,
    876             encoding=ioargs.encoding,
    877             errors=errors,
    878             newline="",
    879         )
    880     else:
    881         # Binary mode
    882         handle = open(handle, ioargs.mode)

FileNotFoundError: [Errno 2] No such file or directory: 'ceda_202107151833.csv'
```

2.1 Introduction

The Historical Data Digital Toolkit (HDDT) comprises of data extracted from one or more ordered datasets (which can be data sourced from several archives). Mulitple donor datasets must share a common data field to enable datasets from multiple donors to be linked together (combined). For this project the common data field is a person's name. Data extracted from the RAI, QFHS and my own research (at RAI and Friends House, London), produced records where each record provided data about a person. All of the persons in this project were members of the Centres for the Emergence of the Discipline of Anthropology in Britain 1830 to 1870 (the CEDA).

Collected data (after cleaning and combining) was then rendered as CSV sheets and these were used to creatre SQL database tables.

The person columns 'Family Name' and 'First Names' in the database are common to all datatables. Therefore the person table is the 'master' table (all persons recorded have a unique ID, and authority index concerns were resolved by accepting the RAI dataset as the project authority index). Attributable data was then attached to the person table (such as date of birth).

Other related data items are captured in relatable tables and all relatable tables have a shared structure ('id', 'name', 'notes').

m2m tables were then built linking the person data table to related datatables. m2m tables allow for many to many realtionships.

Note: The m2m_person_ceda table includes the attributable data 'first_year' and 'last_year'.

The person_person table will generate social network graphs, all other m2m_tables will generate bipartite graphs (bigraphs).

2.2 The Entity Relationship Diagram

2.3 ERD statistics

6 CEDA Societies:

1. QCA Quaker Committee on the Aborigines, 31 members.
2. APS Aborigines Protection Society, 1171 members.
3. ESL Ethnological Society of London, 748 members.
4. ASL Anthropological Society of London, 1334 members.
5. AI Anthropological Institute. 610 members.

514 attribute types:

- ceda (6)
- club (68)
- location (83)
- occupation (93)
- person (3095)
- suffix (155)
- religion (4) Only one group is present, 1 = Quaker.
- society (260)

12097 relationships

- m2m_person_ceda (3894)

- m2m_person_club (323)
- m2m_person_location (2061)
- m2m_person_occupation (1883)
- m2m_person_person (2099)
- m2m_person_religion (593)
- m2m_person_society (1238)
- m2m_person_suffix (1351) *Not used in this project*

2.4 The structure and dimensions of all SQL

tables

Table	Rows	Columns
ceda	6	1
person_ceda	3894	4
club	68	1
person_club	323	2
location	83	1
person_location	2061	2
occupation	93	1
person_occupation	1883	2
person	3095	7
person_person	2099	3
religion	4	1
person_religion	593	3
society	260	1
person_society	1238	2

Note:

Bipartite relationships = 9992 (+2099 person_person relationships = 12091 total relationships)

2.5 The CEDA

code cells

```
ceda
```

	id	name	notes
0	1	QCA	NaN
1	2	APS	NaN
2	3	ESL	NaN
3	4	ASL	NaN
4	5	LAS	NaN
5	6	AI	NaN

```
person_ceda
```

	id	person_id	ceda_id	first_year	last_year	notes
0	1	5	3	1844	1844	NaN
1	2	7	3	1844	1844	NaN
2	3	8	3	1858	1871	NaN
3	4	12	3	1860	1871	NaN
4	5	14	3	1843	1845	NaN
...	...	...	...	...	...	...
3889	4096	3415	2	1839	1850	NaN
3890	4097	3416	2	1861	1862	NaN
3891	4098	3417	2	1853	1856	NaN
3892	4099	3418	2	1840	1840	NaN
3893	4100	3419	2	1840	1867	NaN

3894 rows × 6 columns

2.6 All CEDA members' relationships visualisation

The graph above shows all of the popular bigraph data in the database. Including all data result in a 'hairball' because the network is too dense to be capable of analysis at this (thehighest) level.

1850 members of the community are recorded as members of 35 popular entities (Locations, occupations, societies and the Athenaeum Club). These entities make a sphere of popular interest graph where meetings between members concerning the CEDA may have taken place, equally they may also be places where members might meet up only infrequently or informally.

The visual analysis of connectivity between members in single societies and between members of multiple societies indicates the extent that the community is societally connected. The 1850 make up 60% of the entire community.

2.7 All persons are members of at least one CEDA society

2.8 Memberships in each CEDA table

```
person_ceda.groupby('ceda_id')['person_id'].nunique().plot(kind='bar')
plt.title ("CEDA memberships")
plt.xlabel ("CEDA")
plt.ylabel ("Number of persons")
plt.show()
```

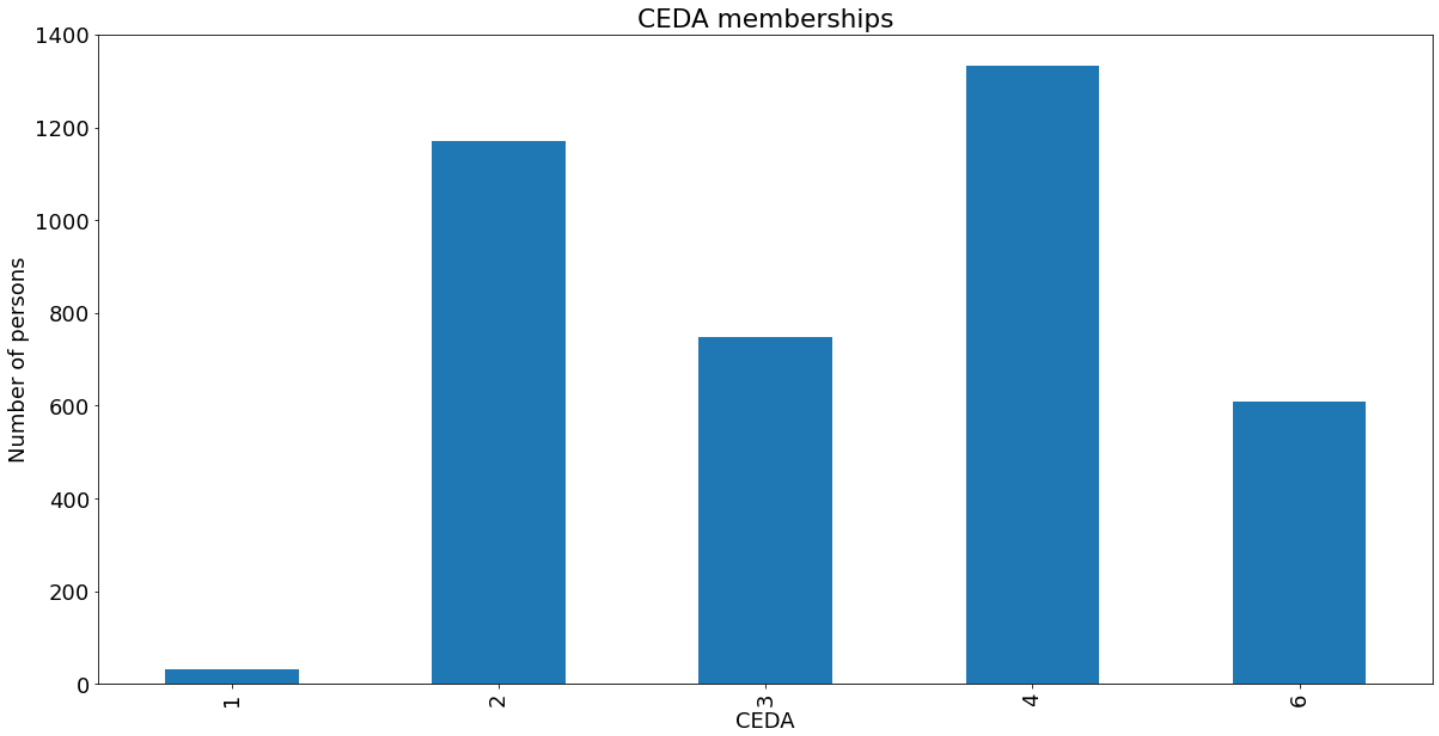


Chart (above) Memberships by CEDA society. - 1 QCA, - 2 APS, - 3 ESL, - 4 ASL, - 6 AI

Note: 5 - LAS data has not been collected by the RAI archivists

2.9 CEDA members were also members of 68 clubs

```
club
```

	id	name	notes
0	2	Athenaeum Club	NaN
1	3	Marlborough Club	NaN
2	4	Carlton Club	NaN
3	5	Oriental Club	NaN
4	6	National Club	NaN
...	...	...	...
63	65	Royal Albert Yacht Club	NaN
64	66	Berwickshire Naturalists Field Club	NaN
65	67	Indian Club	NaN
66	68	Ad Eundem	NaN
67	69	Arthurs Club	NaN

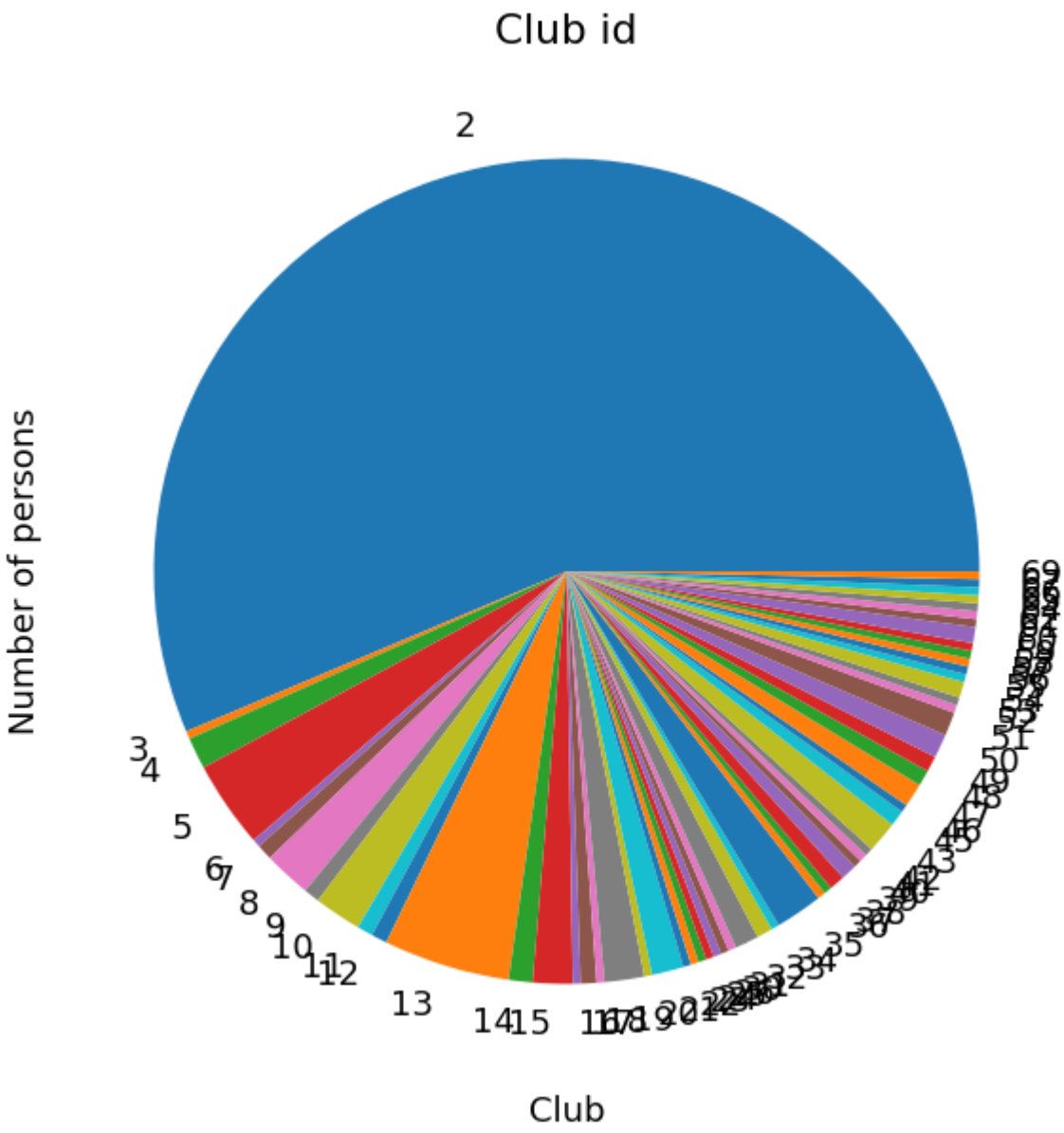
68 rows × 3 columns

```
person_club
```

	id	person_id	club_id
0	1	7	2
1	2	22	2
2	3	33	2
3	4	33	3
4	5	33	4
...	...	...	...
318	356	2163	5
319	357	2196	2
320	358	2214	4
321	359	2223	2
322	360	2251	2

323 rows × 3 columns

```
person_club.groupby('club_id')['person_id'].nunique().plot(kind='pie')
plt.title ("Club id")
plt.xlabel ("Club")
plt.ylabel ("Number of persons")
plt.show()
```



The Athaneum Club membrship (2) exceeds that of all other clubs combined.

Note - ignore clubs outside of the top 5?

Clubs will not be analysed in this project but the Athenaeum club can be used as an attribute (because it is a singularity).

2.10 CEDA members are identified with 83

locations

```
location
```

	id	name	notes
0	1	London	NaN
1	3	country	NaN
2	4	Africa	NaN
3	5	America	NaN
4	6	Scotland	NaN
...	...	...	...
78	80	Madagascar	NaN
79	81	Ecuador	NaN
80	82	Seychelles	NaN
81	83	Panama	NaN
82	84	Armenia	NaN

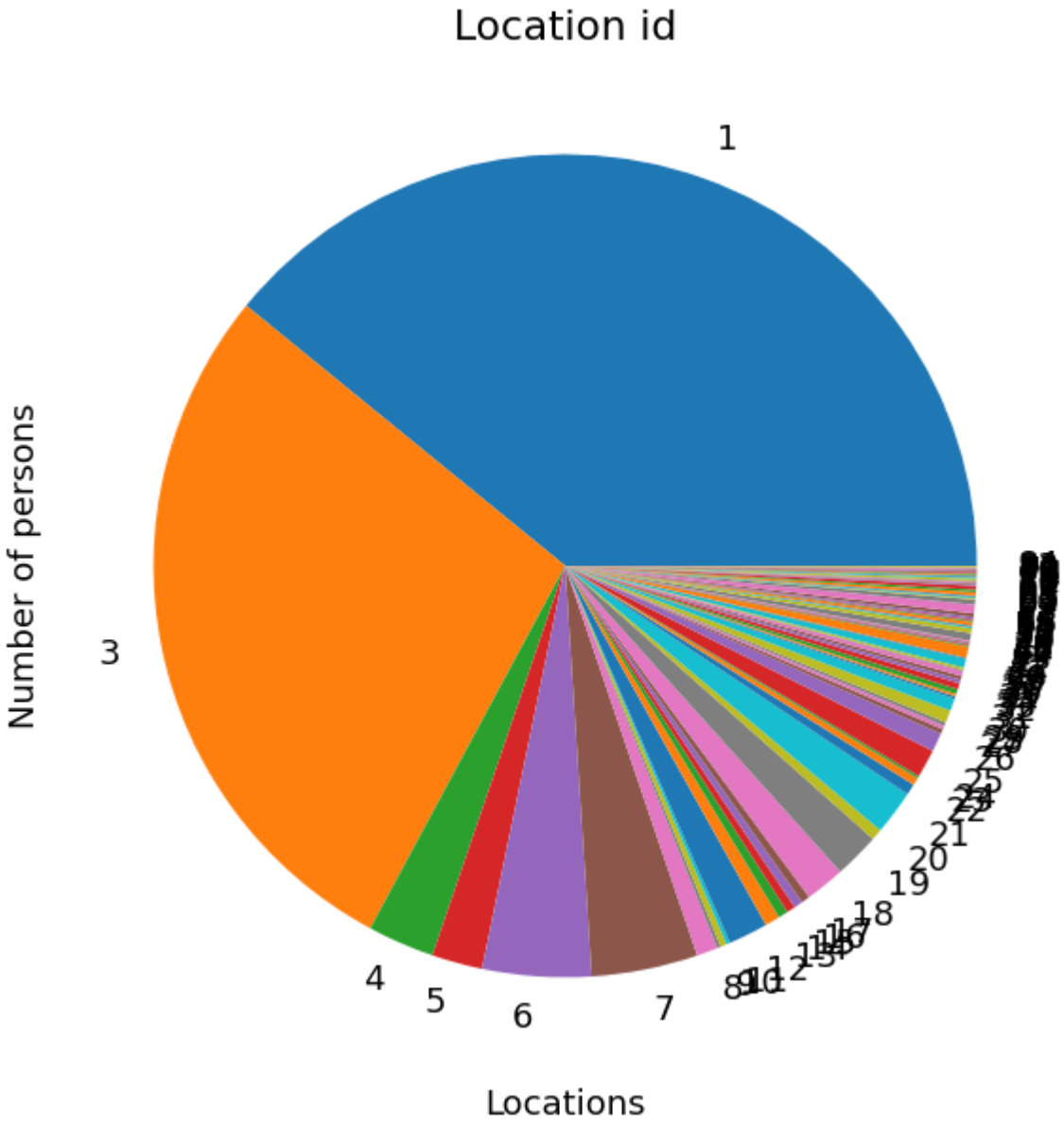
83 rows × 3 columns

```
person_location
```

	id	person_id	location_id
0	1	1	1
1	2	3	3
2	3	4	4
3	4	6	1
4	5	8	1
...	...	...	...
2056	2257	2255	1
2057	2259	2258	3
2058	2260	2259	83
2059	2261	2260	84
2060	2262	2260	31

2061 rows × 3 columns

```
person_location.groupby('location_id')['person_id'].nunique().plot(kind='pie')
plt.title ("Location id")
plt.xlabel ("Locations")
plt.ylabel ("Number of persons")
plt.show()
```


Location id
1
3
4
5
6
7
18
19
20
21
Number of persons
Locations

Location ID	location	Count
1	London	806
3	country	578
6	Scotland	88
7	India	86
4	Africa	54
5	America	41

Location ID	location	Count
19	Germany	37
21	France	36
12	Ireland	32
18	Australia	32
25	Wales	23

Locations table. Note: London, Country and Scotland equal 1472, more than 50% of all locations

2.11 top 10 locations

2.12 Some persons are associated with mulitple locations

We can see that London and ‘country’(sic) are the most populated locations. Because the ‘country’ location is an aggregate (and not a specific location) we can think of London and ‘country’ as a twin centre. Within the twin centre we can see the members of both London and ‘country’ locations and that the members of each are highly networked. We can also see that the London location contains many members who have no association with any other group (including ‘country’). London 1830 - 1870, was densely populated and so it is possible that members of the London location had other modes of association. Because the ‘country’ location is an aggregate we cannot make the same analysis to the same extent, it is possible that many members in (say) Newcastle had no association with other members in (say) Bristol. We can see the large group of members who were members of both London and ‘country’ locations. It is highly likely that these members served as conduits of

communication and group cohesion. It is interesting to note that only 3 members of this London and ‘country’ group were members of groups outside of the twin centre.

Eight other location each have a membership of around 30 members (we can call these the satellites), all of the satellite groups relate directly to the twin centre with very few members associated with more that one satellite location.

Australia and Ireland have associations with both London and ‘country’. The German location is most closely associated with the ‘country’ group. All of the other locations are strongly associated with the London location.

Germany (far right) is the location least associated with London. Alex Nidda Genthe is the only member from Germany who is also a member of the London location. Friedrich Max Muller, Frederick Augustus Haverick and Gustav Oppert each network with ‘country’ members. William Wilson Hunter is the only ‘country’ member who also appears in the Germany location. He and Gustav oppert also have a location connection with India.

2.13 CEDA members occupations

```
occupation
```

	id	name	notes
0	1	literary	NaN
1	3	medical	NaN
2	4	armed services	NaN
3	5	political	NaN
4	6	church	NaN
...	...	...	...
88	90	farmer	NaN
89	91	clockmaker	NaN
90	92	plant collector	NaN
91	93	private means	NaN
92	94	oceanographer	NaN

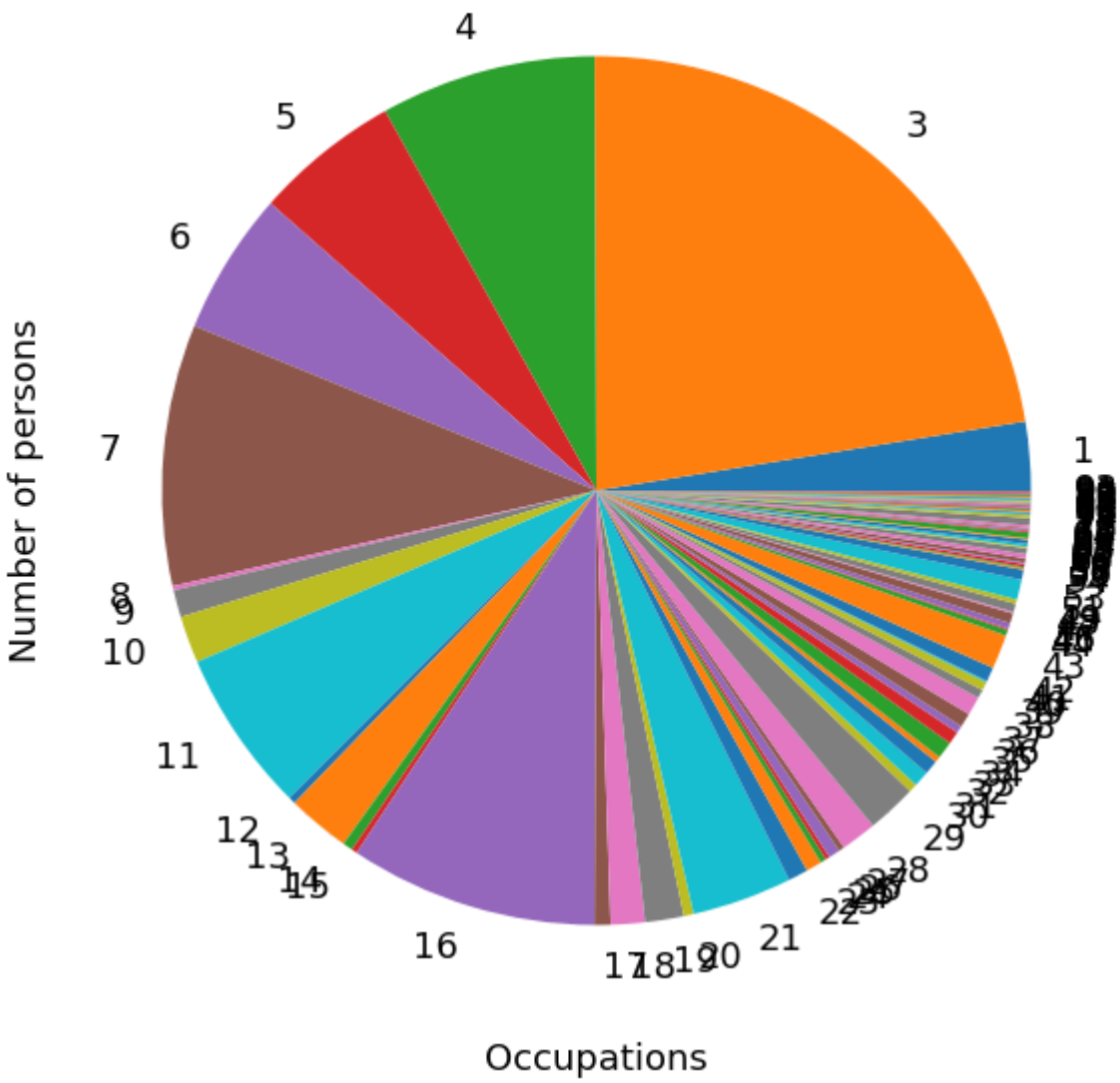
93 rows × 3 columns

```
person_occupation
```

	id	person_id	occupation_id
0	1	1	1
1	2	3	3
2	3	3	4
3	4	5	5
4	5	8	3
...	...	...	...
1878	2122	2252	3
1879	2123	2253	3
1880	2124	2254	3
1881	2125	2255	16
1882	2127	2259	13

1883 rows × 3 columns

```
person_occupation.groupby('occupation_id')['person_id'].nunique().plot(kind='pie')
plt.title ("Occupation id")
plt.xlabel ("Occupations")
plt.ylabel ("Number of persons")
plt.show()
```


Occupation id
Number of persons
Occupations
1
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
29
30
38
43

Occupation ID	occupation	Number
3	medical	424
7		academic
16	business	174
4	armed services	151
11	legal	114
5	political	102

Occupation ID	occupation	Number
6	church	100
21	aristocracy	70
1	literary	48
13	diplomacy	44
29	administrative	35

Table - The top 11 occupations

2.14 the top 10 Occupations

2.15 Some members have more than one occupation

We can see that ‘medical’,‘academic’ and ‘armed services’ together account for half of the members by occupation. We can also see that the largest three occupational categories each contain many members who have no association with any other occupational group. We can see that the medical categories contain many members who are also members of the other two principal categories (‘academic’ and ‘armed services’). It is highly likely that these members served as conduits of communication and group cohesion amongst the three principal occupational cegories.

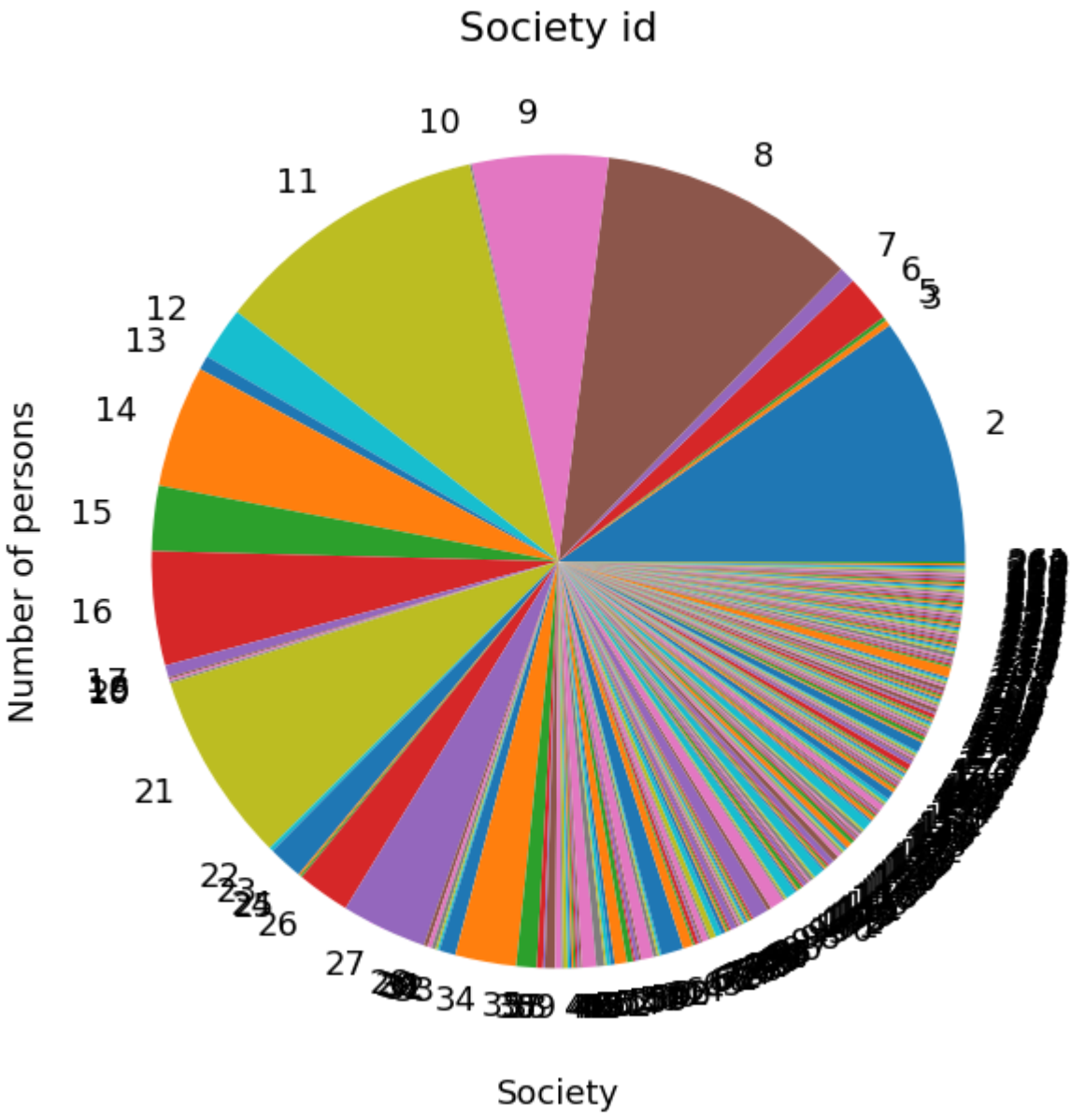
Seven other occupations each have a range of members with literary the lowest and business the highest. All of the satellite groups relate directly to the triple centre with many members also associated with more that one other satellite occupation.

It is surprising the the least networked occupation is ‘church’ and perhaps less so that ‘business’ and ‘legal’are highly networked.

Several individuals form a web of interconnectedness between the members occupations.

2.16 Society memberships

```
person_society.groupby('society_id')['person_id'].nunique().plot(kind='pie')
plt.title ("Society id")
plt.xlabel ("Society")
plt.ylabel ("Number of persons")
plt.show()
```



2.17 Top 10 Society memberships

2.18 Some CEDA members are members of multiple societies

We can see that ‘Geological Society’ and the ‘Royal Goegraphical Society’ together account for a significant number of members by society. The ‘Royal College of Surgeons’, the ‘Medical and Chirurgical Society’ and the ‘College of Physicians’ form the next largest cluster of memberships of societies. These two clusters each contain many members who have no association with any other society. We can see that the medical group and the geographical group have few members in common. The ‘Royal Society’ and the ‘Linnean Society’ in the centre have between them the greatest level of networking amongst all of the societies. It is highly likely that these members served as conduits of communication and group cohesion amongst the two principal society groups.

Many other societies have a range of members all of whom are highly interconnected. All of the satellite groups relate most closely to the ‘Royal Society’ and the ‘Linnean Society’ rather than to the two larger clusters. Many members of the smaller satellite societies are also associated with more that one other satellite occupation.

It is surprising the the least networked occupation is the ‘Royal College of Surgeons’ and perhaps less so that the ‘Geological Society’ and the ‘Royal Geographical Society’ are highly networked.

Several individuals form a web of interconnectedness between the members of societies.

2.19 All Quaker relationships

```
person_person
```

	id	relationship_type_id	person1_id	person2_id
0	1	1	23	2346
1	2	1	2264	2346
2	3	1	2265	2547
3	4	1	2545	2547
4	5	1	2546	2547
...	...	...	...	...
2094	4373	3	2494	2496
2095	4374	3	2495	2579
2096	4376	3	2867	2868
2097	4378	3	2869	2871
2098	4382	3	2503	2876

2099 rows × 4 columns

2.20 Quaker family relationships

```
person_person.groupby('relationship_type_id')['id'].nunique().plot(kind='bar')
plt.title ("Person to Person Relationships")
plt.xlabel ("Relationship Types")
plt.ylabel ("Number of persons")
plt.show()
```

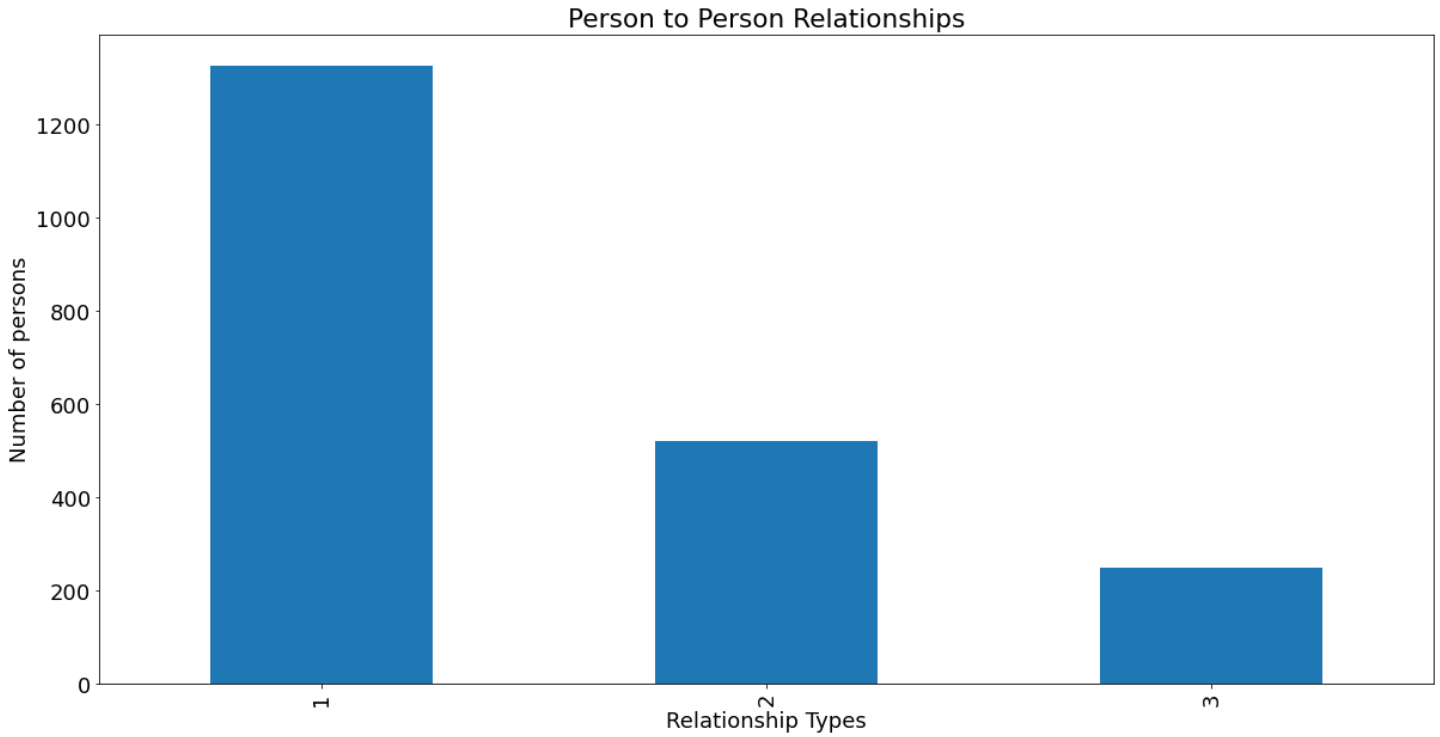


Chart above Person to person relationships (Quakers only)

Key - 1 = Distant relations, 2 = Close relations, 3 = Immediate relations

2.21 Quaker members of the CEDA

2.22 - All SQL relatable tables rendered in Gephi format

Rendering data in Gephi format

JNB uses NetworkX to generate GexF files for data to be used to produce graph files for network analysis in Gephi. Two files must be generated:

1. A file of 'Names' listing the names of all nodes to be used in a graph (These are 'persons' and all entities in related data tables, such as 'occupations'). Each row in a Names table must be unique and referenced in the 'Tuples' (or edges) table.

Note - For Names to be Gephi compliant the headers 'family_name' and 'first_names' must be combined into a single header -'Names'.

2. A 'Tuples' (or edges) table made up of two columns of Names where the two Names are related. The first column must be headed 'Source' and the second column 'Target'.

'Names' and 'Tuples' tables can also have an 'id' column (if not then Gephi will assign one).

Note - Because 'Names', 'Source' and 'Target' are language names in Gephi capitalisation is important.

SQL views have been written to convert the data tables into Gephi standard.

```
gephi_all_names
```

	ID	Source	Target
0	1	Arthur William A Beckett	ASL
1	1	Arthur William A Beckett	London
2	1	Arthur William A Beckett	literary
3	3	Andrew Mercer Adam	ASL
4	3	Andrew Mercer Adam	armed services
...	...	...	...
9987	3415	x Wright	APS
9988	3416	W Wrigley	APS
9989	3417	James Yates	APS
9990	3418	John Young	APS
9991	3419	Thomas Zachary	APS

9992 rows × 3 columns

```
gephi_names_notceda
```

	ID	Source	Target
0	1	Arthur William A Beckett	London
1	1	Arthur William A Beckett	literary
2	3	Andrew Mercer Adam	armed services
3	3	Andrew Mercer Adam	country
4	3	Andrew Mercer Adam	medical
...	...	...	...
6093	2876	Joshua Wilson	Quaker
6094	2877	F Woodhead	Quaker
6095	2878	W Woolston	Quaker
6096	2879	Francis Wright	Quaker
6097	2880	S W Wright	Quaker

6098 rows × 3 columns

```
gephi_person_ceda
```

	ID	Source	Target
0	5	William Adam	ESL
1	7	William (1) Adams	ESL
2	8	William (2) Adams	ESL
3	12	Louis Agassiz	ESL
4	14	Augustine Aglio	ESL
...	...	...	...
3889	3415	x Wright	APS
3890	3416	W Wrigley	APS
3891	3417	James Yates	APS
3892	3418	John Young	APS
3893	3419	Thomas Zachary	APS

3894 rows × 3 columns

```
gephi_person_club
```

	ID	Source	Target
0	7	William (1) Adams	Athenaeum Club
1	22	Rutherford Alcock	Athenaeum Club
2	33	William Amhurst Tyssen Amhurst	Athenaeum Club
3	33	William Amhurst Tyssen Amhurst	Marlborough Club
4	33	William Amhurst Tyssen Amhurst	Carlton Club
...	...	...	...
318	2163	James Whishaw	Oriental Club
319	2196	S W D Williams	Athenaeum Club
320	2214	William Smith Windham	Carlton Club
321	2223	Henry Drummond Wolff	Athenaeum Club
322	2251	Ashton Yates	Athenaeum Club

323 rows × 3 columns

```
gephi_person_location
```

	ID	Source	Target
0	1	Arthur William A Beckett	London
1	3	Andrew Mercer Adam	country
2	4	H R Adam	Africa
3	6	Henry John Adams	London
4	8	William (2) Adams	London
...	...	...	...
2056	2255	James A Youl	London
2057	2258	Robert Younge	country
2058	2259	Arthur de Zeltner	Panama
2059	2260	x Zohrab	Armenia
2060	2260	x Zohrab	Turkey

2061 rows × 3 columns

```
gephi_person_occupation
```

	ID	Source	Target
0	1	Arthur William A Beckett	literary
1	3	Andrew Mercer Adam	medical
2	3	Andrew Mercer Adam	armed services
3	5	William Adam	political
4	8	William (2) Adams	medical
...	...	...	...
1878	2252	W Holt Yates	medical
1879	2253	James Yearsley	medical
1880	2254	Stephen Yeldham	medical
1881	2255	James A Youl	business
1882	2259	Arthur de Zeltner	diplomacy

1883 rows × 3 columns

```
gephi_person_person
```

	id	Source	Target
0	1	William Aldam	x Fox
1	2	William Jun Aldam	x Fox
2	3	Frederick Alexander	R D Alexander
3	4	G W Alexander	R D Alexander
4	5	Henry Alexander	R D Alexander
...	...	...	...
2094	4373	Alfred Waterhouse	R Waterhouse
2095	4374	Mary Waterhouse	Paul Bevan
2096	4376	Lucy Westcombe	Thomas Westcombe
2097	4378	Benjamin Wheeler	Samuel Wheeler
2098	4382	Charles Wilson	Joshua Wilson

2099 rows × 3 columns

```
gephi_person_religion
```

	ID	Source	Target
0	2233	William Spicer Wood	Quaker
1	2211	William Wilson	Quaker
2	2208	James Wilson	Quaker
3	2108	E T Wakefield	Quaker
4	1744	John Ross	Quaker
...	...	...	...
588	2876	Joshua Wilson	Quaker
589	2877	F Woodhead	Quaker
590	2878	W Woolston	Quaker
591	2879	Francis Wright	Quaker
592	2880	S W Wright	Quaker

593 rows × 3 columns

```
gephi_person_society
```

	ID	Source	Target
0	8	William (2) Adams	Royal College of Surgeons
1	8	William (2) Adams	Pathological Society of London
2	8	William (2) Adams	Medical Society of London
3	8	William (2) Adams	Medical and Chirurgical Society of London
4	11	William Adlam	Somersetshire Archaeological and Natural Histo...
...	...	...	...
1233	2245	William Cort Wright	Manchester Literary and Philosophical Society
1234	2245	William Cort Wright	Chemical Society
1235	2252	W Holt Yates	Royal College of Physicians
1236	2258	Robert Younge	York Philosphical Society
1237	2258	Robert Younge	Linnean Society of London

1238 rows × 3 columns

P7 Chapter 3 HDDT Using SQLite database standard ‘views’

Index of views, dataframe info and rendering corrections

Thesis Chapter 6.19.6

jnb_ceda_database_views

Generic code block used to set up every notebook

```
# First we call up the python packages we need to perform the analysis:

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from operator import itemgetter
import networkx as nx
from networkx.algorithms import community #This part of networkx, for community det
import nbconvert
import csv

# to add an image <img src="xxxx.png">

# to jump to another paragraph <a id='another_cell'></a>

# to Insert a hyperlink [https://github.com/KelvinBeerJones](https://github.com/Kel

# Convert float64 to INT64;   table['column'] = table['column'].fillna(0).astype(np
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[1], line 5
      3 import pandas as pd
      4 import numpy as np
----> 5 import matplotlib.pyplot as plt
      6 from operator import itemgetter
      7 import networkx as nx

ModuleNotFoundError: No module named 'matplotlib'
```

Generic code block used to make gexf file from dataframes

```
with open('vw_3_bipartite_names.csv', 'r') as nodecsv: # Open the file
    nodereader = csv.reader(nodecsv) # Read the csv
    nodes = [n for n in nodereader][1:]  # Retrieve the data
    #using Python list comprhension and list slicing to remove the header row.

node_names = [n[0] for n in nodes] # Get a list of only the node names

with open('vw_3_bipartite_nodes.csv', 'r') as edgecsv: # Open the file
    edgereader = csv.reader(edgecsv) # Read the csv
    edges = [tuple(e) for e in edgereader][1:]  # Retrieve the data
```

```
#nodes
```

```
#edges
```

```
print(len(node_names))
print(len(edges))
```

```
3094
514
```

```
G = nx.Graph()
G.add_nodes_from(node_names)
G.add_edges_from(edges)
print(nx.info(G))
```

```
Name:
Type: Graph
Number of nodes: 3869
Number of edges: 514
Average degree:   0.2657
```

```
nx.write_gexf(G, 'project_name')
```

3.1 Introduction and explanation

3.1.1 Introduction

In the HDDT methodology Jupyter Notebooks (JNB) are used to visualise dataframes, each of which is generated from a SQLite 'view'. JNB is used to generate charts and graphs using Pyplot and Seaborn libraries and also to generate GexF files for Gephi.

SQLite database views have been built to comprehensively 'map' the structure of the database as shown in the Entity Relationship Diagram below. Views capture:

1. Individual Name data tables - such as persons, occupations, locations, clubs and societies. Note: religion here is solely an attribute of persons (because the HDDT currently only captures Quakers). Religion would become a meaningful data table if other religious affiliations were also captured. Data tables form ‘Name’ tables (and Names are also known as Nodes depending on which technology is open - SQLite, JNB or Gephi).
2. Tuples tables that show many to many relationships. These are person Name(s) and their relationship to other Name(s) (occupation, location, club and society) and they are made of pairs of nodes, which combined are called a tuple in the form of ‘person Name (is asociated with) other Name’. Persons here are also known as ‘Source’ and the associatey d Name(s) as ‘Target’.
3. Both Name and Tuple tables can have attributes attached. In Gephi attributes attached to records in a Names table will allow filtering based on Nodes whereas attributes attached to individual records in Tuples tables will allow filtering of edges based on attributes. A GexF file can contain attributes for both Names and Tuples.

Note - First letter capitalisation in the HDDT must be followed. The Gephi dictionary requires Name, Source and Target to be in this form.

The process:

1. Devise a set of comprehensive database views (Using DBeaver).
2. Export the views as csv files to the container ‘jnd_ceda_database_sql_views’.
3. This container is also is a GitHub repo to enable version control.
4. This Jupyter Notebook is located here (all resources necessary for a JNB must be in the same container).
5. Use JNB to make a dataframe for each csv file and display the first 10 records.
6. Check the dataframe info to ensure that no tables have columns rendered as float64. (Apply the method: table[‘column’] = table[‘column’].fillna(0).astype(np.int64) to covert float64 to int64 if necessary.
7. Make subsets of dataframes to slice the data. (Use SQLIte database select queries to make INNER and LEFT joins between tables)

3.1.2 Explanation

This workbook resides in a GitHub container facilitating version control. Each time this workbook is amended a record is made in the corresponding GitHub repo.

Gephi requires a Names file (generated by Networkx), and this comprises of all Nodes irrespective of which side of an EDGE they will later be attached to. In the Edges file in Gephi the Names now become Nodes paired as Tuples (Source and Target) and Gephi infers an Edge between them. Person names and bipartite group names are variously called - Names, Nodes, Source and Target depending where they are being used.

Names files in Gephi. Names can have attributes and these can be used to style Nodes.

Tuples in Gephi format = First column must be “Source”, second column must be “Target”, additional columns are ‘attributes’ of each tuple. (Note: attributes will be used in Gephi to style edges and not nodes.)

All dataframes consist of data types OBJECT and INT64 only. CSV sheets occasionally render columns that render as FLOAT64. Where this occurs a fix is applied immeditely after the pd.read_csv command.

3.2 To make a new project

1. Make a new project repo in Github.
2. Clone the new project repo to a new container in the HDDT workspace.
3. Create a JNB notebook in the new container workspace.
4. Copy selected csv files from this container to the new container.
5. In the new JNB use routines to validate selected data.-
    1. pd.read_csv,
    2. df.iloc [0:10]
    3. df.info ()
6. Use this routine to correct float64 columns. df[‘column’] = df[‘column’].fillna(0).astype(np.int64)

7. Slice data as needed and make a new df of the subset data.
8. Use pandas to make graphs of the data.
9. If wanted use the routine df.to_csv ('vw_hddt_newdataframe.csv') to put a csv of the subset of a dataframe in the new workspace container.
10. If wanted make a GefX file (in the new workspace container) to use Gephi for data visualisation.
11. Don't forget to use VSC to update Github for version control if changes are made to the csv files in this container or this jnb for version control and to make latest version available to all users.

Links to sections in this workbook

Table
Person Table
Person Attributes
Person names and other nodes combined
Other Nodes
Bigraph aa tuples
Religion tuples
Location tuples
Occupation tuples
Society tuples
Club tuples
CEDA Name attributes
CEDA tuples
CEDA tuples attributes
Quakers
Quaker immediate
Quaker close
Quaker distant
Quaker CEDA tuples

3.3 Entity Relationship Diagram

3.4 Person table (3094 records)

Dataframe

```
person_table = pd.read_csv ('vw_hddt_person_table.csv')
person_table ['gender_id'] = person_table ['gender_id'].fillna(0).astype(np.int64)
person_table ['birth_year'] = person_table ['birth_year'].fillna(0).astype(np.int64
person_table['death_year'] = person_table['death_year'].fillna(0).astype(np.int64)
```

```
person_table.iloc [0:10]
```

	Name	title	gender_id	birth_year	death_year	data_source_id	notes
0	Arthur William A Beckett	NaN	1	1844	1909	1	17 King Street, S. James's, S.W. 88 St James's...
1	Andrew Mercer Adam	NaN	1	0	0	1	Boston, Lincolnshire
2	H R Adam	NaN	1	0	0	1	Old Calabar, W. Africa
3	William Adam	NaN	1	0	0	1	NaN
4	Henry John Adams	NaN	1	0	0	1	14 Thornhill Square, N.
5	William (1) Adams	NaN	1	0	0	1	NaN
6	William (2) Adams	NaN	1	1820	1900	1	5 Henrietta Street Cavendish Square [1862]7 L...
7	William Adlam	NaN	1	0	0	1	9 Brook Street, Bath [1863]Manor House, Chew ....
8	Louis Agassiz	NaN	1	1807	1873	1	Cambridge Mass
9	Anastasius Agathides	NaN	1	1805	1881	1	28 Kildare Terr. Westbourne Park, W [A3]1861A...

```
person_table.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3094 entries, 0 to 3093
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Name            3094 non-null   object
 1   title           776 non-null    object
 2   gender_id       3094 non-null   int64 
 3   birth_year      3094 non-null   int64 
 4   death_year      3094 non-null   int64 
 5   data_source_id  3094 non-null   int64 
 6   notes           1770 non-null   object
dtypes: int64(4), object(3)
memory usage: 169.3+ KB
```

3.5 Person Names (3094 records)

Datatable

```
person_name = pd.read_csv ('vw_hddt_person_name.csv')
```

```
person_name.iloc [0:10]
```

	Name
0	Arthur William A Beckett
1	Andrew Mercer Adam
2	H R Adam
3	William Adam
4	Henry John Adams
5	William (1) Adams
6	William (2) Adams
7	William Adlam
8	Louis Agassiz
9	Anastasius Agathides

```
person_name.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3094 entries, 0 to 3093
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Name    3094 non-null   object
dtypes: object(1)
memory usage: 24.3+ KB
```

3.6 Persons with attributes (Names file) (3094 records)

Datatable

```
person_attributes = pd.read_csv ('vw_hddt_person_attributes_religion.csv')
person_attributes ['religion_1_quaker'] = person_attributes ['religion_1_quaker'].f
person_attributes ['birth_year'] = person_attributes ['birth_year'].fillna(0).astyp
person_attributes['death_year'] = person_attributes['death_year'].fillna(0).astype(
```

```
person_attributes.iloc [0:10]
```

	Name	birth_year	death_year	religion_1_quaker
0	Arthur William A Beckett	1844	1909	0
1	Andrew Mercer Adam	0	0	0
2	H R Adam	0	0	0
3	William Adam	0	0	0
4	Henry John Adams	0	0	0
5	William (1) Adams	0	0	0
6	William (2) Adams	1820	1900	0
7	William Adlam	0	0	0
8	Louis Agassiz	1807	1873	0
9	Anastasius Agathides	1805	1881	0

```
person_attributes.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3094 entries, 0 to 3093
Data columns (total 4 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   Name               3094 non-null   object
 1   birth_year         3094 non-null   int64 
 2   death_year         3094 non-null   int64 
 3   religion_1_quaker  3094 non-null   int64 
dtypes: int64(3), object(1)
memory usage: 96.8+ KB
```

3.7 All Names (Nodes) (3608 records)

Dataframe

All person names (3095) and bipartite nodes (514) in Gephi ‘Names’ format. Can be used with a ‘tuples’ file to generate a GexF file for Gephi where all possible nodes would appear on the visualisation, including nodes with no associated tuple.

```
all_names_and_nodes = pd.read_csv('vw_hddt_all_names_and_nodes.csv')
```

```
all_names_and_nodes.loc [0:10]
```

	Name
0	Joseph Storrs
1	A Mackintosh Shaw
2	A de Fullner
3	A , jun Ramsay
4	A A Stewart
5	A Ambrose
6	A B Stark
7	A B Wright
8	A Bell
9	A C Brebner
10	A Crowley

```
all_names_and_nodes.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3608 entries, 0 to 3607
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Name    3608 non-null   object
dtypes: object(1)
memory usage: 28.3+ KB
```

3.8 All bipartite Names (514 records)

Dataframe

Bigraph nodes in Gephi Name format. This is a subset of ‘all_names_and_nodes’

```
bigraph_nodes = pd.read_csv ('vw_hddt_bigraph_nodes.csv')
```

```
bigraph_nodes.iloc [0:10]
```

	Name
0	AI
1	APS
2	ASL
3	Aberdeen Horticultural Society
4	Academia Quirurgia of Madrid
5	Academie Hongroise de Pest
6	Academy of Anatolia
7	Academy of Medicine and Surgery of Madrid and ...
8	Academy of Natural Sciences Philadelphia
9	Academy of Natural Sciences of Spain

```
bigraph_nodes.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 514 entries, 0 to 513
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Name    514 non-null    object
dtypes: object(1)
memory usage: 4.1+ KB
```

3.9 All Names (Nodes) as Tuples (9989 records)

dataframe

All tuples from the HDDT in Gephi format. (There are 9991 edges between the 3095 persons and the 514 Bipartite nodes.)

```
bigraph_all_tuples = pd.read_csv ('vw_hddt_all_bigraph_tuples.csv')
```

```
bigraph_all_tuples.iloc [0:10]
```

	Source	Target
0	Joseph Storrs	QCA
1	Joseph Storrs	Quaker
2	A Mackintosh Shaw	ASL
3	A Mackintosh Shaw	country
4	A de Fullner	AI
5	A , jun Ramsay	AI
6	A , jun Ramsay	ASL
7	A , jun Ramsay	Geological Society
8	A , jun Ramsay	London
9	A A Stewart	ASL

```
bigraph_all_tuples.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9989 entries, 0 to 9988
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Source  9989 non-null   object
 1   Target  9989 non-null   object
dtypes: object(2)
memory usage: 156.2+ KB
```

3.10 Religion tuples (592 records)

Dataframe

Quakers

```
religion_tuples = pd.read_csv ('vw_hddt_religion_tuples.csv')
```

```
religion_tuples.iloc [0:10]
```

	Source	Target
0	William Spicer Wood	Quaker
1	William Wilson	Quaker
2	James Wilson	Quaker
3	E T Wakefield	Quaker
4	John Ross	Quaker
5	J Robinson	Quaker
6	William Horton Lloyd	Quaker
7	Joseph Lister	Quaker
8	Jonathan Hutchinson	Quaker
9	William Holmes	Quaker

```
religion_tuples.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 592 entries, 0 to 591
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Source  592 non-null    object
 1   Target  592 non-null    object
dtypes: object(2)
memory usage: 9.4+ KB
```

3.11 Location tuples (2061 records)

Dataframe

Location (UK but not London)

```
location_tuples = pd.read_csv ('vw_hddt_location_tuples.csv')
```

```
location_tuples.iloc [0:10]
```

	Source	Target
0	Arthur William A Beckett	London
1	Andrew Mercer Adam	country
2	H R Adam	Africa
3	Henry John Adams	London
4	William (2) Adams	London
5	William Adlam	country
6	Louis Agassiz	America
7	Anastasius Agathides	London
8	Joseph Agnew	Scotland
9	William Francis Harrison Ainsworth	London

```
location_tuples.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2061 entries, 0 to 2060
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Source  2061 non-null   object
 1   Target  2061 non-null   object
dtypes: object(2)
memory usage: 32.3+ KB
```

3.12 Occupation tuples (1883 records)

Dataframe

Occupations

```
occupation_tuples = pd.read_csv ('vw_hddt_occupation_tuples.csv')
```

```
occupation_tuples.iloc [0:10]
```

	Source	Target
0	Arthur William A Beckett	literary
1	Andrew Mercer Adam	medical
2	Andrew Mercer Adam	armed services
3	William Adam	political
4	William (2) Adams	medical
5	Louis Agassiz	academic
6	Louis Agassiz	biologist
7	Louis Agassiz	geologist
8	Anastasius Agathides	academic
9	Augustine Aglio	artist

```
occupation_tuples.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1883 entries, 0 to 1882
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Source  1883 non-null   object
 1   Target  1883 non-null   object
dtypes: object(2)
memory usage: 29.5+ KB
```

3.13 Society tuples (1238 records)

Dataframe

Society memberships

```
society_tuples = pd.read_csv ('vw_hddt_society_tuples.csv')
```

```
society_tuples.iloc [0:10]
```

	Source	Target
0	William (2) Adams	Royal College of Surgeons
1	William (2) Adams	Pathological Society of London
2	William (2) Adams	Medical Society of London
3	William (2) Adams	Medical and Chirurgical Society of London
4	William Adlam	Somersetshire Archaeological and Natural Histo...
5	William Francis Harrison Ainsworth	Royal Geographical Society
6	William Francis Harrison Ainsworth	Society of Antiquaries
7	William Francis Harrison Ainsworth	Syro Egyptian Society
8	William Francis Harrison Ainsworth	Geological Society
9	William Baird Airston	Royal College of Surgeons

```
society_tuples.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1238 entries, 0 to 1237
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Source  1238 non-null   object
 1   Target  1238 non-null   object
dtypes: object(2)
memory usage: 19.5+ KB
```

3.14 Club tuples (323 records)

Dataframe

Club memberships

```
club_tuples = pd.read_csv ('vw_hddt_club_tuples.csv')
```

```
club_tuples.iloc [0:10]
```

	Source	Target
0	William (1) Adams	Athenaeum Club
1	Rutherford Alcock	Athenaeum Club
2	William Amhurst Tyssen Amhurst	Athenaeum Club
3	William Amhurst Tyssen Amhurst	Marlborough Club
4	William Amhurst Tyssen Amhurst	Carlton Club
5	William Arbuthnot	Oriental Club
6	Richard Edward Arden	National Club
7	Richard Edward Arden	Junior Athenaeum Club
8	William Armstrong	Athenaeum Club
9	William Henry Ashurst	Reform Club

```
club_tuples.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 323 entries, 0 to 322
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Source  323 non-null    object
 1   Target  323 non-null    object
dtypes: object(2)
memory usage: 5.2+ KB
```

3.15 CEDA tuples (3892 records)

Dataframe

Tuples in Gephi format to graph the memberships of CEDA

```
ceda_tuples = pd.read_csv('vw_hddt_ceda_tuples.csv')
```

```
ceda_tuples.iloc [0:10]
```

	Source	Target
0	William Adam	ESL
1	William (1) Adams	ESL
2	William (2) Adams	ESL
3	Louis Agassiz	ESL
4	Augustine Aglio	ESL
5	William Francis Harrison Ainsworth	ESL
6	Alexander Muirhead Aitken	ESL
7	Rutherford Alcock	ESL
8	William Aldam	ESL
9	William Allen	ESL

```
ceda_tuples.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3892 entries, 0 to 3891
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Source  3892 non-null   object
 1   Target  3892 non-null   object
dtypes: object(2)
memory usage: 60.9+ KB
```

3.16 Quaker Committee on the Aborigines (QCA)

```
qca = ceda_tuples[ceda_tuples["Target"] == "QCA"]
```

```
qca.iloc [0:10]
```

	Source	Target
2732	Thomas (1) Hodgkin	QCA
2998	James Bowden	QCA
2999	William Nash	QCA
3000	Joseph Sturge	QCA
3001	William Jun Grimshaw	QCA
3003	Henry Knight	QCA
3004	Edward Paull	QCA
3005	Robert Jun Alsop	QCA
3006	Abram Rawlinson Barclay	QCA
3007	John Barclay	QCA

```
qca.to_csv ('vw_hddt_ceda_qca.csv')
```

3.17 Aborigines Protection Society (APS)

```
aps = ceda_tuples[ceda_tuples["Target"] == "APS"]
```

```
aps.iloc [0:10]
```

	Source	Target
2692	William Aldam	APS
2693	Samuel C Baker	APS
2694	James Bell	APS
2695	John Bell (2)	APS
2696	John Brown	APS
2697	Henry Christy	APS
2698	Thomas junior Christy	APS
2699	William Clay	APS
2700	Richard King	APS
2701	John James Sturz	APS

```
aps.to_csv ('vw_hddt_ceda_aps.csv')
```

3.18 Ethnological Society of London (ESL)

```
esl = ceda_tuples[ceda_tuples["Target"] == "ESL"]
```

```
esl.iloc [0:10]
```

	Source	Target
0	William Adam	ESL
1	William (1) Adams	ESL
2	William (2) Adams	ESL
3	Louis Agassiz	ESL
4	Augustine Aglio	ESL
5	William Francis Harrison Ainsworth	ESL
6	Alexander Muirhead Aitken	ESL
7	Rutherford Alcock	ESL
8	William Aldam	ESL
9	William Allen	ESL

```
esl.to_csv ('vw_hddt_ceda_esl.csv')
```

3.19 Anthropological Society of London (ASL)

```
asl = ceda_tuples[ceda_tuples["Target"] == "ESL"]
```

```
asl.iloc [0:10]
```

	Source	Target
0	William Adam	ESL
1	William (1) Adams	ESL
2	William (2) Adams	ESL
3	Louis Agassiz	ESL
4	Augustine Aglio	ESL
5	William Francis Harrison Ainsworth	ESL
6	Alexander Muirhead Aitken	ESL
7	Rutherford Alcock	ESL
8	William Aldam	ESL
9	William Allen	ESL

```
asl.to_csv ('vw_hddt_ceda_asl.csv')
```

3.20 Anthropological Institute (AI)

```
ai = ceda_tuples[ceda_tuples["Target"] == "ESL"]
```

```
ai.iloc [0:10]
```

	Source	Target
0	William Adam	ESL
1	William (1) Adams	ESL
2	William (2) Adams	ESL
3	Louis Agassiz	ESL
4	Augustine Aglio	ESL
5	William Francis Harrison Ainsworth	ESL
6	Alexander Muirhead Aitken	ESL
7	Rutherford Alcock	ESL
8	William Aldam	ESL
9	William Allen	ESL

```
ai.to_csv ('vw_hddt_ceda_ai.csv')
```

3.21CEDA Name with attributes (3892 records)

Dataframe

Datatable of all people and their memberships of CEDA (some people are in more than one). Attaches attributes to Nodes in Gephi. (Note: records = greater that 3095 persons due to multiple memberships). Gephi will disregard duplicate Names (but not tuples)

```
ceda_name_attributes = pd.read_csv ('vw_hddt_ceda_name_attributes.csv')
ceda_name_attributes ['quaker'] = ceda_name_attributes ['quaker'].fillna(0).astype(
```

```
ceda_name_attributes.iloc [0:10]
```

	Name	quaker	first_year	last_year	birth_year	death_year
0	William Adam	0	1844	1844	NaN	NaN
1	William (1) Adams	0	1844	1844	NaN	NaN
2	William (2) Adams	0	1858	1871	1,820	1,900
3	Louis Agassiz	0	1860	1871	1,807	1,873
4	Augustine Aglio	0	1843	1845	1,777	1,857
5	William Francis Harrison Ainsworth	0	1856	1860	1,807	1,896
6	Alexander Muirhead Aitken	0	1864	1871	NaN	NaN
7	Rutherford Alcock	0	1862	1871	1,809	1,897
8	William Aldam	1	1844	1848	1,813	1,890
9	William Allen	0	1858	1858	NaN	NaN

```
ceda_name_attributes.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3892 entries, 0 to 3891
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Name        3892 non-null   object
 1   quaker      3892 non-null   int64 
 2   first_year  3892 non-null   int64 
 3   last_year   3892 non-null   int64 
 4   birth_year  1528 non-null   object
 5   death_year  1639 non-null   object
dtypes: int64(3), object(3)
memory usage: 182.6+ KB
```

3.22 CEDA tuples with attributes (3892

records)

Dataframe

CEDA tuples with attrubutes attaches attributes to edges in Gephi.

```
ceda_tuples_attributes = pd.read_csv ('vw_hddt_ceda_tuples_attributes.csv')
```

```
ceda_tuples_attributes.iloc [0:10]
```

	Source	Target	first_year	last_year	birth_year	death_year
0	William Adam	ESL	1844	1844	NaN	NaN
1	William (1) Adams	ESL	1844	1844	NaN	NaN
2	William (2) Adams	ESL	1858	1871	1,820	1,900
3	Louis Agassiz	ESL	1860	1871	1,807	1,873
4	Augustine Aglio	ESL	1843	1845	1,777	1,857
5	William Francis Harrison Ainsworth	ESL	1856	1860	1,807	1,896
6	Alexander Muirhead Aitken	ESL	1864	1871	NaN	NaN
7	Rutherford Alcock	ESL	1862	1871	1,809	1,897
8	William Aldam	ESL	1844	1848	1,813	1,890
9	William Allen	ESL	1858	1858	NaN	NaN

```
ceda_tuples_attributes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3892 entries, 0 to 3891
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Source      3892 non-null   object
 1   Target      3892 non-null   object
 2   first_year  3892 non-null   int64 
 3   last_year   3892 non-null   int64 
 4   birth_year  1528 non-null   object
 5   death_year  1639 non-null   object
dtypes: int64(2), object(4)
memory usage: 182.6+ KB
```

3.23 Quakers (592 records)

Dataframe

```
quakers = pd.read_csv ('vw_hddt_quakers.csv')
quakers ['birth_year'] = quakers ['birth_year'].fillna(0).astype(np.int64)
quakers ['death_year'] = quakers ['death_year'].fillna(0).astype(np.int64)
```

```
quakers.iloc [0:10]
```

	Name	birth_year	death_year
0	William Aldam	1813	1890
1	S Stafford Allen	1840	1870
2	Edward Backhouse	1808	1879
3	James (1) Backhouse	1794	1869
4	James Bell	1818	1872
5	Antonio Brady	1811	1881
6	William Bull	1828	1902
7	Charles Buxton	1823	1871
8	Henry Christy	1810	1865
9	William Clay	1791	1869

```
quakers.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 592 entries, 0 to 591
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Name        592 non-null    object
 1   birth_year  592 non-null    int64 
 2   death_year  592 non-null    int64 
dtypes: int64(2), object(1)
memory usage: 14.0+ KB
```

3.24 Quaker family relationships, (2086 records)

Dataframe

```
person_relationships = pd.read_csv ('vw_hddt_person1_person2.csv')
```

```
person_relationships.iloc [0:10]
```

	Source	Target	relationship_type_id
0	William Aldam	x Fox	1
1	William Jun Aldam	x Fox	1
2	Frederick Alexander	R D Alexander	1
3	G W Alexander	R D Alexander	1
4	Henry Alexander	R D Alexander	1
5	R D Alexander	John M Candler	1
6	Thomas Allis	James Jun Backhouse	1
7	Thomas Allis	Francis Brown	1
8	Thomas Allis	Septimus Warner	1
9	R Arthington	J Gurney Barclay	1

```
person_relationships.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2086 entries, 0 to 2085
Data columns (total 3 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   Source                2086 non-null   object
 1   Target                2086 non-null   object
 2   relationship_type_id  2086 non-null   int64 
dtypes: int64(1), object(2)
memory usage: 49.0+ KB
```

3.25 Quaker immediate relationships (246 records)

Datatable

```
quaker_immediate_relationships = pd.read_csv ('vw_hddt_person_person_immediate.csv'
```

```
quaker_immediate_relationships.iloc [0:10]
```

	'Source'	Target	immediate
0	Source	John M Albright	3
1	Source	Rachel Albright	3
2	Source	William Albright	3
3	Source	John M Albright	3
4	Source	William Albright	3
5	Source	John M Albright	3
6	Source	William Jun Aldam	3
7	Source	G W Alexander	3
8	Source	Henry Alexander	3
9	Source	Henry Alexander	3

```
quaker_immediate_relationships.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 246 entries, 0 to 245
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   'Source'   246 non-null    object
 1   Target     246 non-null    object
 2   immediate  246 non-null    int64 
dtypes: int64(1), object(2)
memory usage: 5.9+ KB
```

3.26 Quakers close relationships (519 records)

Datatable

```
quaker_close_relationships = pd.read_csv ('vw_hddt_person_person_close.csv')
```

```
quaker_close_relationships.iloc [0:10]
```

	'Source'	Target	close
0	Source	Christopher Bowley	2
1	Source	Robert Charleton	2
2	Source	Frederick H Fox	2
3	Source	Thomas Maw	2
4	Source	William Norton	2
5	Source	Algernon Peckover	2
6	Source	Cornelius Hanbury	2
7	Source	Edward Beck	2
8	Source	Cornelius Hanbury	2
9	Source	Martha Lucas	2

```
quaker_close_relationships.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 519 entries, 0 to 518
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   'Source'  519 non-null    object
 1   Target    519 non-null    object
 2   close     519 non-null    int64 
dtypes: int64(1), object(2)
memory usage: 12.3+ KB
```

3.27 Quaker distant relationships (1321 records)

Datatable

```
quaker_distant_relationships = pd.read_csv ('vw_hddt_person_person_distant.csv')
```

```
quaker_distant_relationships.iloc [0:10]
```

	'Source'	Target	distant
0	Source	x Fox	1
1	Source	x Fox	1
2	Source	R D Alexander	1
3	Source	R D Alexander	1
4	Source	R D Alexander	1
5	Source	John M Candler	1
6	Source	James Jun Backhouse	1
7	Source	Francis Brown	1
8	Source	Septimus Warner	1
9	Source	J Gurney Barclay	1

```
quaker_distant_relationships.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1321 entries, 0 to 1320
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   'Source'  1321 non-null   object
 1   Target    1321 non-null   object
 2   distant   1321 non-null   int64 
dtypes: int64(1), object(2)
memory usage: 31.1+ KB
```

3.28 Quaker CEDA membership (tuples) (643 records)

Dataframe

```
quakers_ceda_tuples = pd.read_csv ('vw_hddt_quakers_ceda_tuples.csv')
```

```
quakers_ceda_tuples.iloc [0:10]
```

	Source	Target	religion_name	first_year	last_year
0	William Spicer Wood	APS	Quaker	1864	1867
1	William Spicer Wood	ASL	Quaker	1863	1871
2	William Spicer Wood	AI	Quaker	1863	1871
3	William Wilson	APS	Quaker	1838	1865
4	William Wilson	ASL	Quaker	1865	1866
5	James Wilson	APS	Quaker	1862	1867
6	James Wilson	ASL	Quaker	1865	1865
7	E T Wakefield	APS	Quaker	1853	1864
8	E T Wakefield	ASL	Quaker	1865	1868
9	John Ross	APS	Quaker	1839	1852

```
quakers_ceda_tuples.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 643 entries, 0 to 642
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Source         643 non-null    object
 1   Target         643 non-null    object
 2   religion_name  643 non-null    object
 3   first_year     643 non-null    int64 
 4   last_year      643 non-null    int64 
dtypes: int64(2), object(3)
memory usage: 25.2+ KB
```

3.29 Quakers in the QCA

```
quakers_qca = quakers_ceda_tuples[quakers_ceda_tuples["Target"] == "QCA"]
```

```
quakers_qca
```

	Source	Target	religion_name	first_year	last_year
21	Thomas (1) Hodgkin	QCA	Quaker	1839	1847
287	James Bowden	QCA	Quaker	1842	1847
288	William Nash	QCA	Quaker	1842	1847
289	Joseph Sturge	QCA	Quaker	1842	1847
290	William Jun Grimshaw	QCA	Quaker	1840	1847
291	Henry Knight	QCA	Quaker	1840	1847
293	Edward Paull	QCA	Quaker	1840	1847
294	Robert Jun Alsop	QCA	Quaker	1837	1847
295	Abram Rawlinson Barclay	QCA	Quaker	1837	1839
296	John Barclay	QCA	Quaker	1837	1839
297	Richard Barrett	QCA	Quaker	1837	1839
298	John Thomas Barry	QCA	Quaker	1837	1847
300	Peter Bedford	QCA	Quaker	1837	1847
302	John Bell	QCA	Quaker	1837	1839
304	Thomas Christy	QCA	Quaker	1837	1839
306	Samuel Darton	QCA	Quaker	1837	1839
307	Josiah Forster	QCA	Quaker	1837	1847
309	Robert Forster	QCA	Quaker	1837	1847
311	William Forster	QCA	Quaker	1837	1847
313	Joseph Talwin Foster	QCA	Quaker	1837	1847
314	John Hamilton	QCA	Quaker	1837	1839
315	Edwd Harris	QCA	Quaker	1837	1847
316	Geo Holmes	QCA	Quaker	1837	1839
317	Robert Howard	QCA	Quaker	1837	1839
319	John Kitching	QCA	Quaker	1837	1839
321	Joseph Neatby	QCA	Quaker	1837	1847
323	John Sanderson	QCA	Quaker	1837	1847

	Source	Target	religion_name	first_year	last_year
325	Joseph Shewell	QCA	Quaker	1837	1839
327	George Stacey	QCA	Quaker	1837	1847
328	Joseph Storrs	QCA	Quaker	1837	1847

```
quakers_qca.to_csv ('vw_hddt_ceda_quaker_qca.csv')
```

3.30 Quakers in the APS

```
quakers_aps = quakers_ceda_tuples[quakers_ceda_tuples["Target"] == "APS"]
```

```
quakers_aps.iloc [0:10]
```

	Source	Target	religion_name	first_year	last_year
0	William Spicer Wood	APS	Quaker	1864	1867
3	William Wilson	APS	Quaker	1838	1865
5	James Wilson	APS	Quaker	1862	1867
7	E T Wakefield	APS	Quaker	1853	1864
9	John Ross	APS	Quaker	1839	1852
10	J Robinson	APS	Quaker	1839	1840
12	William Horton Lloyd	APS	Quaker	1862	1862
14	Joseph Lister	APS	Quaker	1851	1855
16	Jonathan Hutchinson	APS	Quaker	1857	1866
19	William Holmes	APS	Quaker	1840	1867

```
quakers_aps.to_csv ('vw_hddt_ceda_quaker_aps.aps')
```

3.31 Quakers in the ESL

```
quakers_esl = quakers_ceda_tuples[quakers_ceda_tuples["Target"] == "ESL"]
```

```
quakers_esl
```

	Source	Target	religion_name	first_year	last_year
13	William Horton Lloyd	ESL	Quaker	1844	1847
15	Joseph Lister	ESL	Quaker	1844	1847
23	Thomas (1) Hodgkin	ESL	Quaker	1844	1862
25	John Henry Gurney	ESL	Quaker	1860	1867
29	Charles Henry Fox	ESL	Quaker	1861	1871
32	William Fowler	ESL	Quaker	1851	1851
34	Robert Nicholas Fowler	ESL	Quaker	1851	1871
39	David Dale	ESL	Quaker	1860	1863
44	x Collier	ESL	Quaker	1844	1844
46	William Clay	ESL	Quaker	1861	1868
48	Henry Christy	ESL	Quaker	1854	1865
58	James Bell	ESL	Quaker	1852	1862
60	James (1) Backhouse	ESL	Quaker	1869	1869
62	Edward Backhouse	ESL	Quaker	1870	1871
67	William Aldam	ESL	Quaker	1844	1848

```
quakers_esl.to_csv ('vw_hddt_ceda_quaker_esl.csv')
```

3.32 Quakers in the ASL

```
quakers_asl = quakers_ceda_tuples[quakers_ceda_tuples["Target"] == "ASL"]
```

```
quakers_asl
```

	Source	Target	religion_name	first_year	last_year
1	William Spicer Wood	ASL	Quaker	1863	1871
4	William Wilson	ASL	Quaker	1865	1866
6	James Wilson	ASL	Quaker	1865	1865
8	E T Wakefield	ASL	Quaker	1865	1868
11	J Robinson	ASL	Quaker	1865	1865
17	Jonathan Hutchinson	ASL	Quaker	1863	1871
20	William Holmes	ASL	Quaker	1865	1869
27	George Stacey Gibson	ASL	Quaker	1864	1866
37	James T J Doyle	ASL	Quaker	1865	1868
41	Henry Crowley	ASL	Quaker	1864	1871
50	Charles Buxton	ASL	Quaker	1864	1866
52	William Bull	ASL	Quaker	1867	1871
55	Antonio Brady	ASL	Quaker	1864	1871
65	S Stafford Allen	ASL	Quaker	1863	1870

```
quakers_asl.to_csv ('vw_hddt_ceda_quaker_asl.csv')
```

3.33 Quakers in the AI

```
quakers_ai = quakers_ceda_tuples[quakers_ceda_tuples["Target"] == "AI"]
```

```
quakers_ai
```

	Source	Target	religion_name	first_year	last_year
2	William Spicer Wood	AI	Quaker	1863	1871
18	Jonathan Hutchinson	AI	Quaker	1863	1871
30	Charles Henry Fox	AI	Quaker	1861	1871
35	Robert Nicholas Fowler	AI	Quaker	1851	1871
42	Henry Crowley	AI	Quaker	1864	1871
53	William Bull	AI	Quaker	1867	1871
56	Antonio Brady	AI	Quaker	1864	1871
63	Edward Backhouse	AI	Quaker	1870	1871

```
quakers_ai.to_csv ('vw_hddt_ceda_quaker_ai.csv')
```

P7 Chapter 4 Case Study 1 The Centres for the Emergence of the Discipline of Anthropology (CEDA)

Thesis Chapter 6 Section 6.20

File name: jnb_hddt_ceda_dyn_edges

4.1 HDDT Visualisations - CEDA bigraph

This project explores 4 of 5 ‘foundation societies’ recognised by RAI, and 1 ‘origin’ society (the CQA) add by me.

Society	abv.	Dates
Quaker Committee on the Aborigines*	QCA	1832/37 - 1846
Aborigines Protection Society	APS	1837 - 1919
Ethnological Society of London	ESL	1843 - 1871
Anthropological Society of London	ASL	1863 - 1871
Anthropological Institute	AI	1843 - 1871
London Anthropological Society**	LAS	1873 - 1874

- Origin Society included in this project but not recognised by RAI. ** not included in this project (beyond 1871 cut off date).

```
import csv
from operator import itemgetter
import networkx as nx
from networkx.algorithms import community #This part of networkx, for community det
#needs to be imported separately.
import nbconvert
import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (12, 6)
import seaborn as sn
import numpy as np

plt.rcParams.update({'font.size': 18})

plt.rc('figure', figsize=(20, 10))
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[1], line 3
      1 import csv
      2 from operator import itemgetter
----> 3 import networkx as nx
      4 from networkx.algorithms import community #This part of networkx, for commu
      5 #needs to be imported separately.

ModuleNotFoundError: No module named 'networkx'
```

4.2 The CEDA 1830 - 1870

4.3 The Quaker Committee on the Aborigines (QCA) 1837 -1846

Because there are only 30 members of the QCA we can iist all of them here

The Quaker committee on the Aborigines, was a Quaker Committee of Enquiry. A committee formed by, and exclusively manned by Quakers. It met, performed its enquiries and reported its findings and recommendations to the Quaker Meetings for Sufferings, the standing committee of London Yearly Meeting which was the National Assembly of Quakers in Britain at the time. The committees remit, rules of engagement and characteristics woiuld have been agreed by the national assembly and the committee would no doubt have reported in the manner of Friends. The committee was formed to explore and take up a ‘concern’ amongst Quakers, initially to consider promoting the Gospel amongst the aborigines in 1832 (prompted by similar actions popular at the time among other evangelical churches). But it changed its remit in 1837 to instead take up a philanthropic concern deriving from the group’s increasing awareness through its activities of the plight of aborigines. Therefore, what began as a Quaker Committee of Enquiry to consider promoting the Gospel to Aborigines, soon transformed into the Quaker Committee on the Aborigines, concerned with the plight of the aborigines throughout the colonies, and it’s relief.

```
qca = pd.read_csv ('vw_4_ceda_membership_quakers_qca2.csv')
qca['birth_year'] = qca ['birth_year'].fillna(0).astype(np.int64)
qca['death_year'] = qca['death_year'].fillna(0).astype(np.int64)
qca.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   Name                    30 non-null     object
 1   birth_year              30 non-null     int64 
 2   death_year              30 non-null     int64 
 3   religion_name           30 non-null     object
 4   ceda_name               30 non-null     object
 5   person_ceda_first_year  30 non-null     int64 
 6   person_ceda_last_year   30 non-null     int64 
dtypes: int64(4), object(3)
memory usage: 1.8+ KB
```

```
qca
```

	Name	birth_year	death_year	religion_name	ceda_name	person_ceda_first
0	Thomas (1) Hodgkin	1798	1866	Quaker	QCA	
1	James Bowden	0	0	Quaker	QCA	
2	William Nash	0	0	Quaker	QCA	
3	Joseph Sturge	0	0	Quaker	QCA	
4	William Jun Grimshaw	0	0	Quaker	QCA	
5	Henry Knight	0	0	Quaker	QCA	
6	Edward Paull	0	0	Quaker	QCA	
7	Robert Jun Alsop	0	0	Quaker	QCA	
8	Abram Rawlinson Barclay	0	0	Quaker	QCA	
9	John Barclay	0	0	Quaker	QCA	
10	Richard Barrett	0	0	Quaker	QCA	
11	John Thomas Barry	0	0	Quaker	QCA	
12	Peter Bedford	0	0	Quaker	QCA	
13	John Bell	0	0	Quaker	QCA	
14	Thomas Christy	0	0	Quaker	QCA	
15	Samuel Darton	0	0	Quaker	QCA	

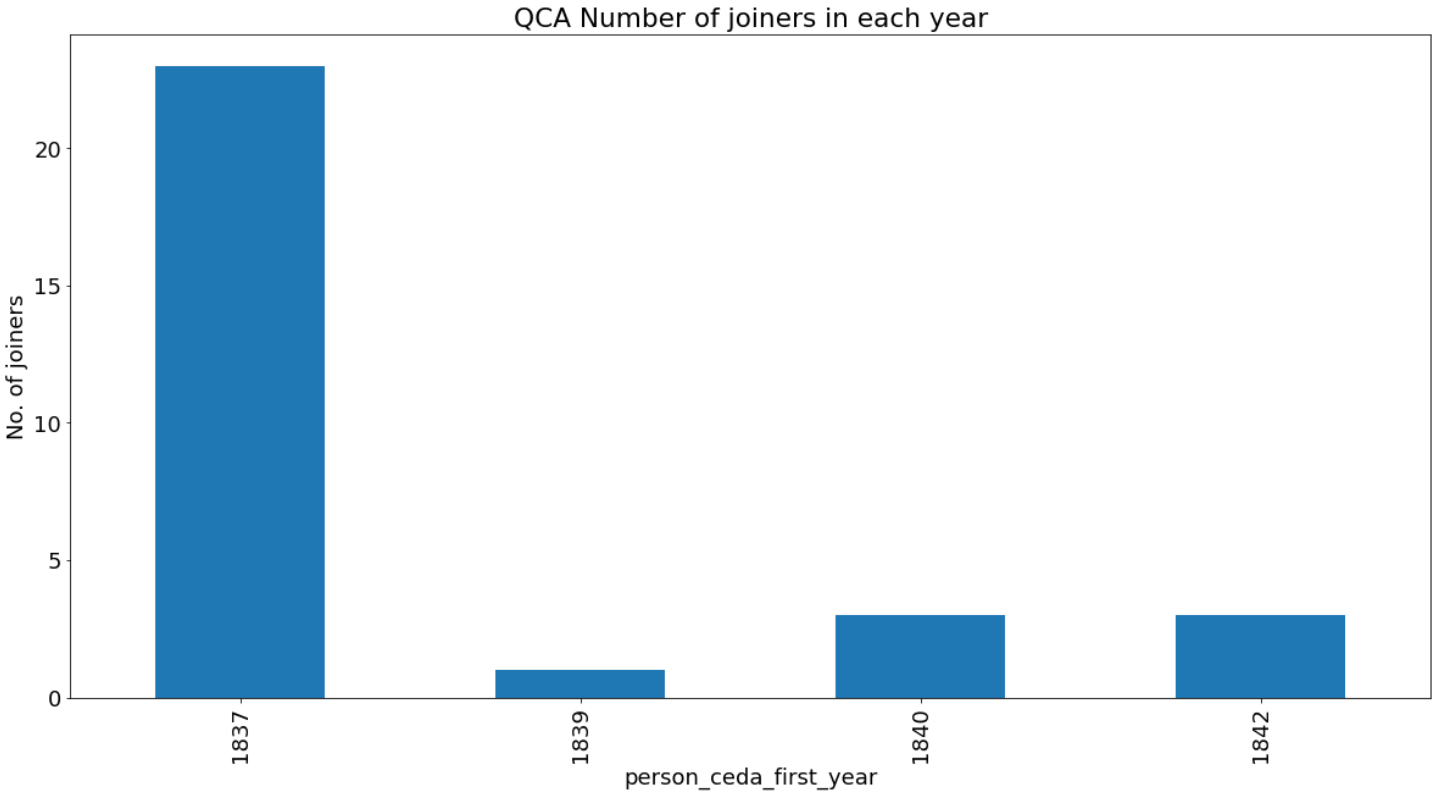
	Name	birth_year	death_year	religion_name	ceda_name	person_ceda_first
16	Josiah Forster	0	0	Quaker	QCA	
17	Robert Forster	0	0	Quaker	QCA	
18	William Forster	0	0	Quaker	QCA	
19	Joseph Talwin Foster	0	0	Quaker	QCA	
20	John Hamilton	0	0	Quaker	QCA	
21	Edwd Harris	0	0	Quaker	QCA	
22	Geo Holmes	0	0	Quaker	QCA	
23	Robert Howard	0	0	Quaker	QCA	
24	John Kitching	0	0	Quaker	QCA	
25	Joseph Neatby	0	0	Quaker	QCA	
26	John Sanderson	0	0	Quaker	QCA	
27	Joseph Shewell	0	0	Quaker	QCA	
28	George Stacey	0	0	Quaker	QCA	
29	Joseph Storrs	0	0	Quaker	QCA	

4.4 CQA Joiners each year

We can plot the number of joiners in each year. New members joined only in the years 1837, 1839, 1840 and 1842. We know that the QCA was established in 1837, so there were only three years

when new members joined.

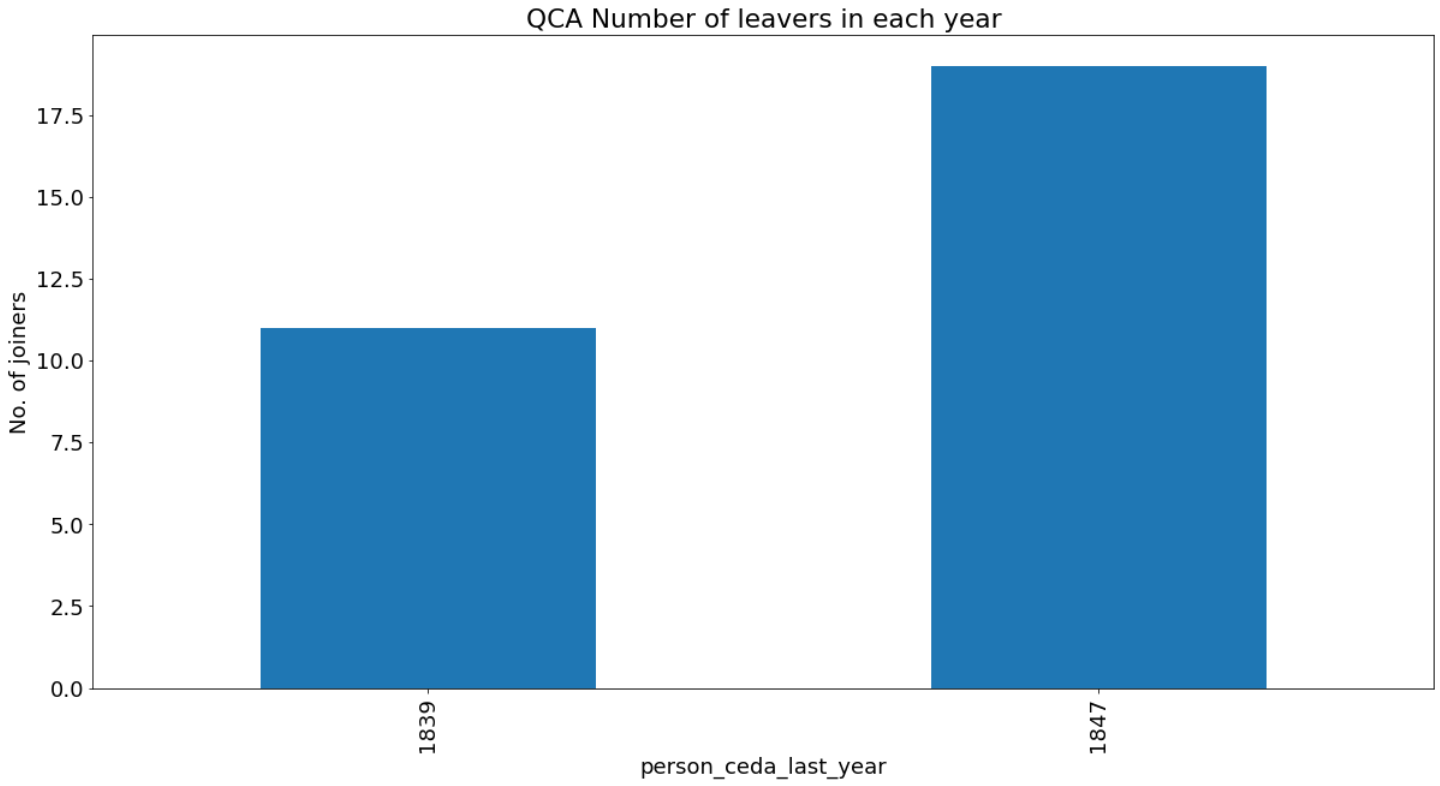
```
qca.groupby('person_ceda_first_year')['Name'].nunique().plot(kind='bar')
plt.title ("QCA Number of joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



4.5 CQA Leavers each year

Because new members group in specific years, we chart the number of leavers in each year. Members left in 1839, 1842 1nd 1847. we know that the QCA was 'laid down' (disbanded) in 1847 which leaves only two years when members left the committee.

```
qca.groupby('person_ceda_last_year')['Name'].nunique().plot(kind='bar')
plt.title ("QCA Number of leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



We can elsewhere investigate why in 1839, 11 members left and 1 joined (Thomas Hodgkin). 3 more joined in each of 1840 and 1842.

4.6 Duration in the CEDA

```
qca[(qca['person_ceda_first_year'] == 1837) & (qca['person_ceda_last_year'] == 1847
```

	Name	birth_year	death_year	religion_name	ceda_name	person_ceda_first
7	Robert Jun Alsop	0	0	Quaker	QCA	
11	John Thomas Barry	0	0	Quaker	QCA	
12	Peter Bedford	0	0	Quaker	QCA	
16	Josiah Forster	0	0	Quaker	QCA	
17	Robert Forster	0	0	Quaker	QCA	
18	William Forster	0	0	Quaker	QCA	
19	Joseph Talwin Foster	0	0	Quaker	QCA	
21	Edwd Harris	0	0	Quaker	QCA	
25	Joseph Neatby	0	0	Quaker	QCA	
26	John Sanderson	0	0	Quaker	QCA	
28	George Stacey	0	0	Quaker	QCA	
29	Joseph Storrs	0	0	Quaker	QCA	

12 of the original members were members throughout the life of the committee. 11 of the original members left after the first year. 3 new members in 1840 and 3 new members in 1841.In any year the majority of members were ‘permanent’ members.

4.7 The Aborigines Protection Society (APS) 1837 -1919

The database contains the names of 1171 members of the APS from its foundation in 1838 to 1871 when it merged with Anti-Slavery International. 571 members (49%) are Quaker.

The Aborigines Protection Society was a secular pressure group that lobbied the Colonial Office and Parliament for the relief of the plight of aborigines throughout the British Settlements. It had a mixed Quaker and non-Quaker executive, membership and subscription lists (it was in large part drawn from the Quaker Committee on the Aborigines), and Quakers dominated the agenda and publishing and lobbying activities of the society for at least the first 30 years of the Society's life. The Society met, performed its enquiries and reported its findings and recommendations to the Society's members according to its own constitution (it usually met monthly). The Society's remit, rules of engagement and characteristics were similar to those of the many other secular lobbying and public opinion forming societies of the time.

```
aps = pd.read_csv ('vw_4_ceda_membership_dates_aps.csv')
aps['birth_year'] = aps ['birth_year'].fillna(0).astype(np.int64)
aps['death_year'] = aps['death_year'].fillna(0).astype(np.int64)
aps.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1170 entries, 0 to 1169
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Name        1170 non-null   object
 1   birth_year  1170 non-null   int64 
 2   death_year  1170 non-null   int64 
 3   Target      1170 non-null   object
 4   first_year  1170 non-null   int64 
 5   last_year   1170 non-null   int64 
dtypes: int64(4), object(2)
memory usage: 55.0+ KB
```

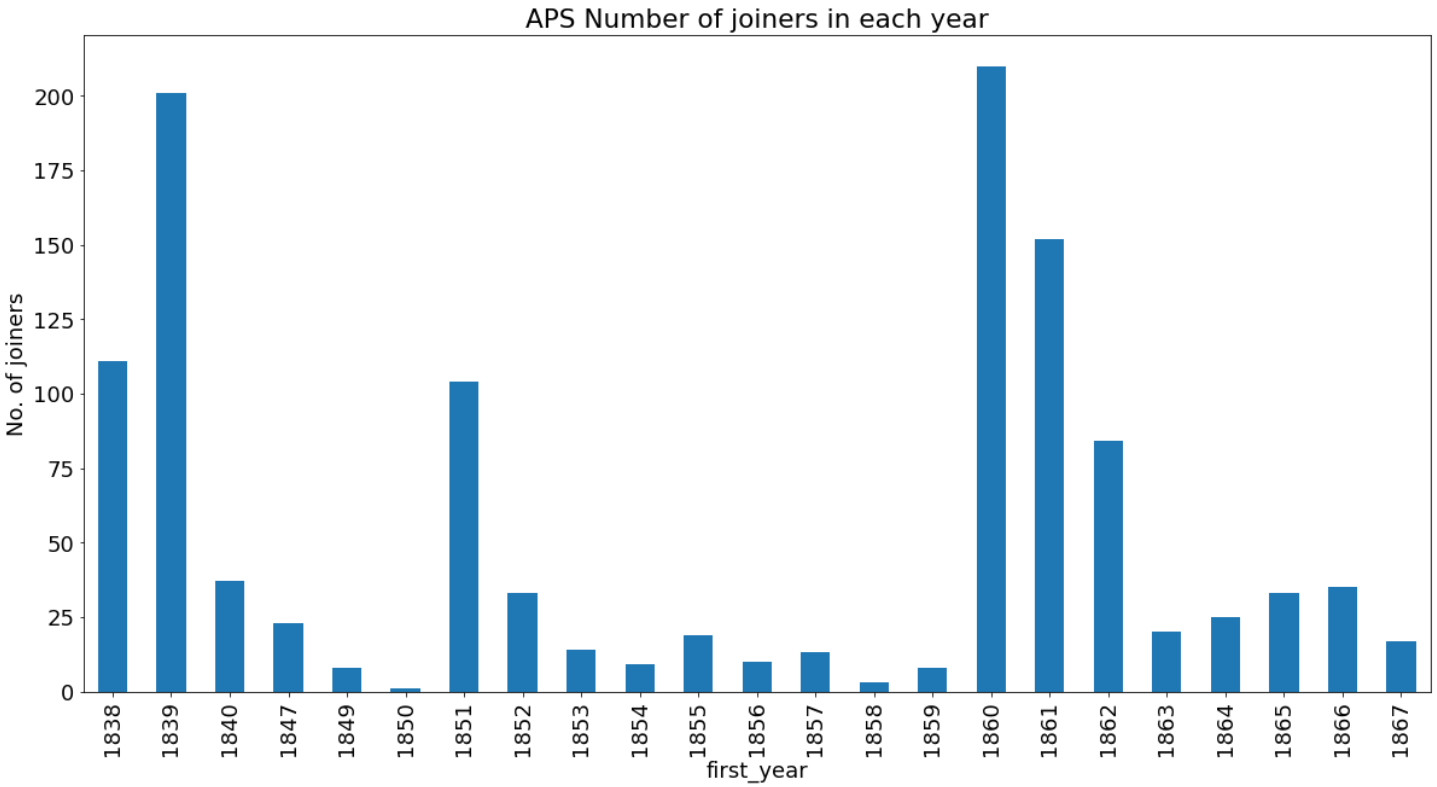
```
aps
```

	Name	birth_year	death_year	Target	first_year	last_year
0	William Aldam	1813	1890	APS	1838	1848
1	Samuel C Baker	1821	1893	APS	1839	1871
2	James Bell	1818	1872	APS	1847	1862
3	John Bell (2)	1811	1895	APS	1838	1855
4	John Brown	1801	1879	APS	1839	1839
...	...	...	...	...	...	...
1165	x Wright	0	0	APS	1839	1850
1166	W Wrigley	0	0	APS	1861	1862
1167	James Yates	0	0	APS	1853	1856
1168	John Young	0	0	APS	1840	1840
1169	Thomas Zachary	0	0	APS	1840	1867

1170 rows × 6 columns

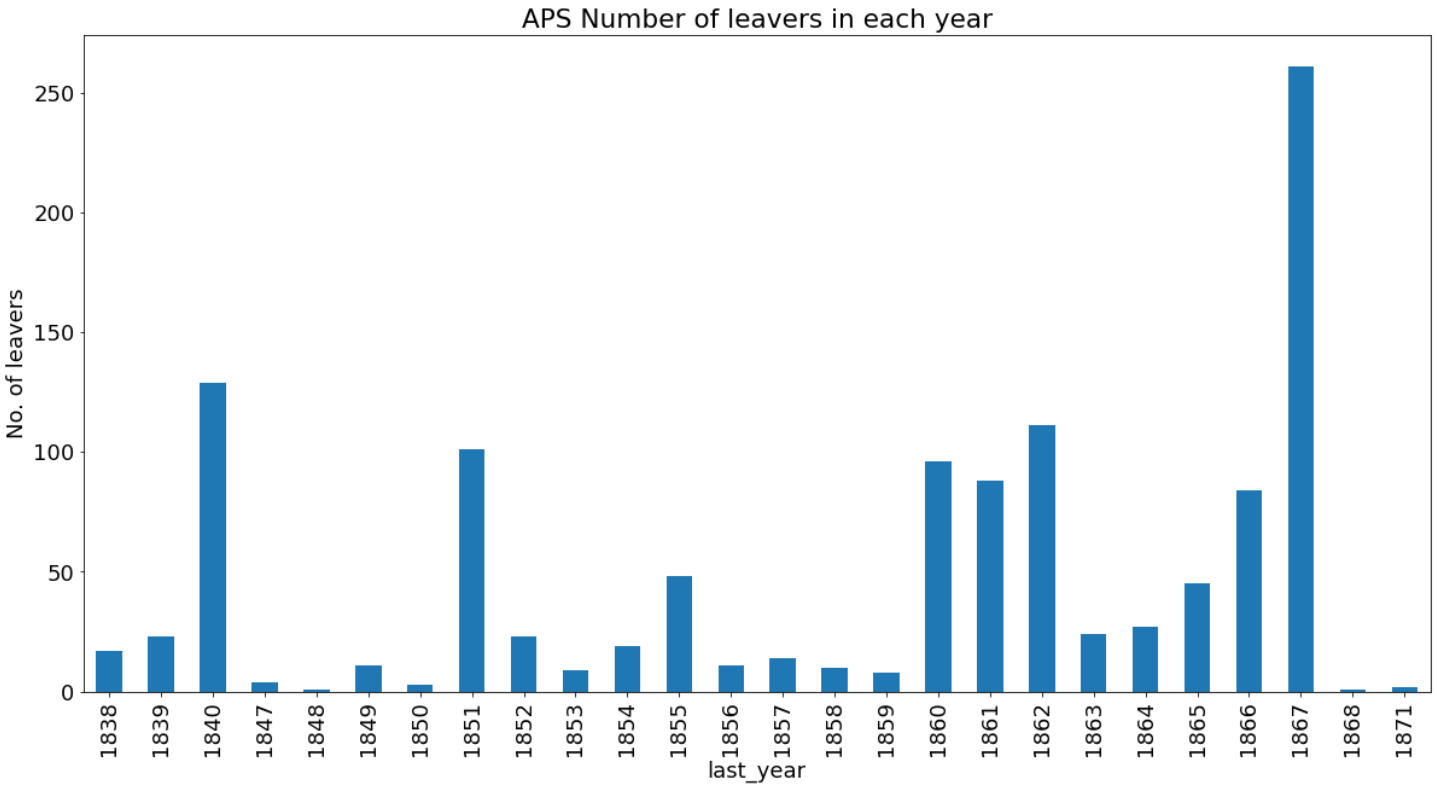
4.8 APS joiners in each year

```
aps.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("APS Number of joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



4.9 APS leavers in each year

```
aps.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("APS Number of leavers in each year")
plt.ylabel ("No. of leavers")
plt.show()
```



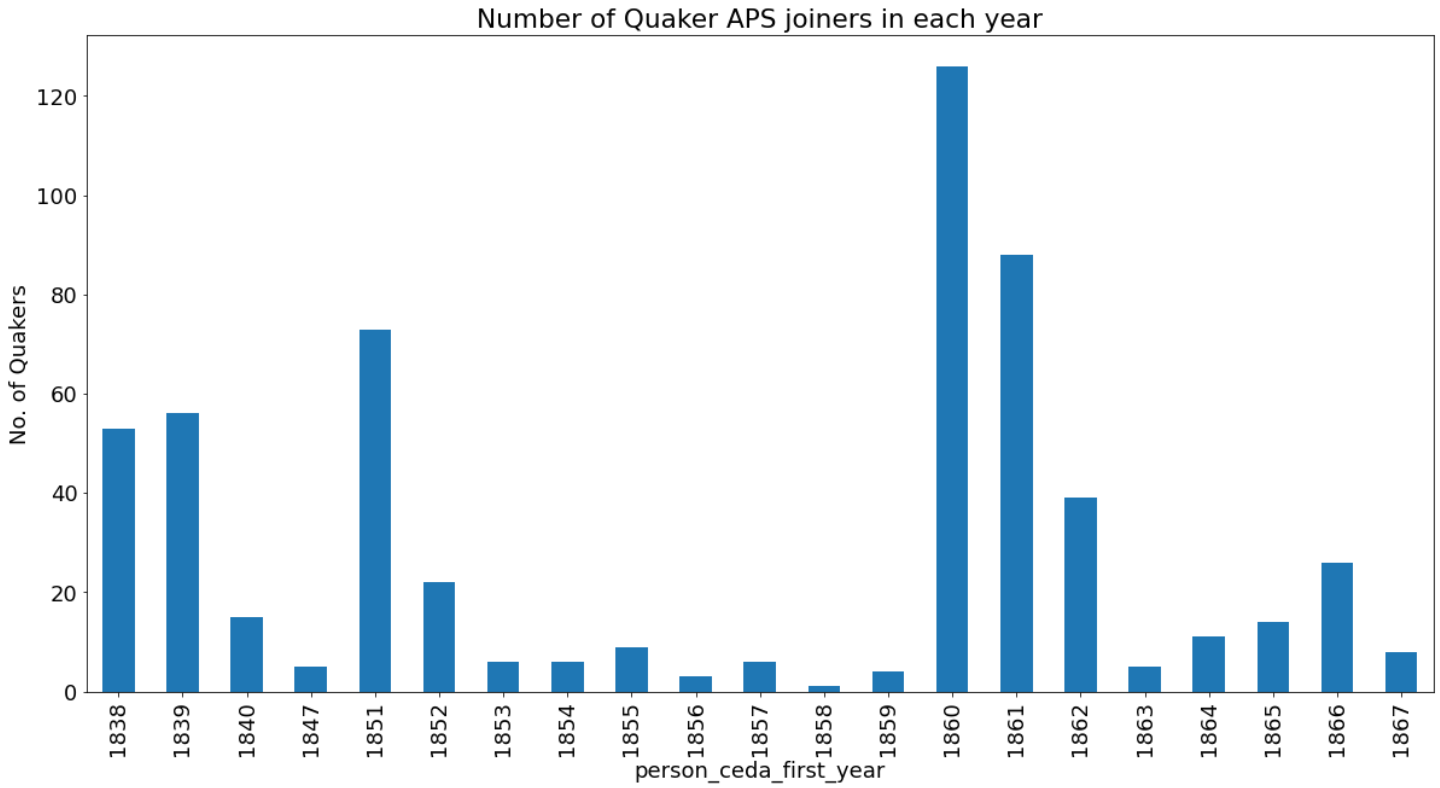

```
quakers_aps = pd.read_csv ('vw_4_ceda_membership_quakers_aps2.csv')
# quakers_aps = aps.loc[aps ['religion_name'] == 'Quaker',:]
quakers_aps
```

	Name	birth_year	death_year	religion_name	ceda_name	person_ceda_firs
0	William Spicer Wood	NaN	1902.0	Quaker	APS	
1	William Wilson	1785.0	1868.0	Quaker	APS	
2	James Wilson	NaN	NaN	Quaker	APS	
3	E T Wakefield	NaN	NaN	Quaker	APS	
4	John Ross	NaN	NaN	Quaker	APS	
...	...	...	...	...	...	
571	Joshua Wilson	NaN	NaN	Quaker	APS	
572	F Woodhead	NaN	NaN	Quaker	APS	
573	W Woolston	NaN	NaN	Quaker	APS	
574	Francis Wright	NaN	NaN	Quaker	APS	
575	S W Wright	NaN	NaN	Quaker	APS	

576 rows × 7 columns

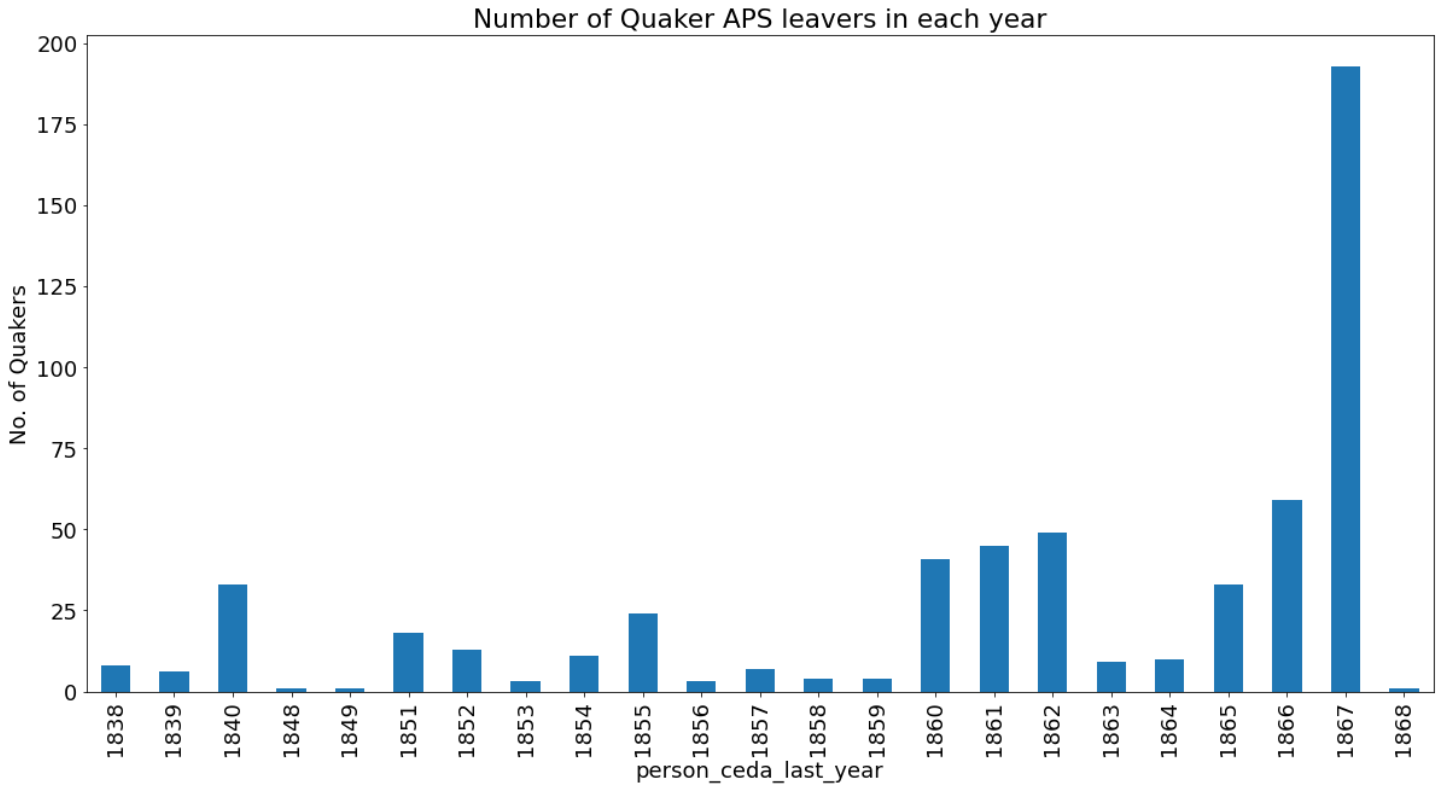
4.10 Quakers joining the APS in each year

```
quakers_aps.groupby('person_ceda_first_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker APS joiners in each year")
plt.ylabel ("No. of Quakers")
plt.show()
```



4.11 Quakers leaving the APS in each year

```
quakers_aps.groupby('person_ceda_last_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker APS leavers in each year")
plt.ylabel ("No. of Quakers")
plt.show()
```



4.12 The Ethnological Society of London (ESL) 1843 - 1871

The Ethnological Society of London was the first intentionally academic society devoted to the discipline of anthropology in Britain. Secular by intent but if not always entirely so in its early years, it sought to be a place where those with a scientific interest in the field of ethnology could commune, share ideas and knowledge, and produce academic reports and hold academic meetings. It met, performed its enquiries and reported its findings and recommendations to the Society's members according to its own constitution (it usually met monthly). The Society's remit, rules of engagement and characteristics were those of the many other scientific societies emerging at the time, its constitution being purposely compliant with BAAS requirements.

```
esl = pd.read_csv ('vw_4_ceda_membership_dates_esl.csv')

# code not needed for this set because in this datframe birth_year and death_year s
#esl['birth_year'] = esl ['birth_year'].fillna(0).astype(np.int64)
#esl['death_year'] = esl['death_year'].fillna(0).astype(np.int64)
# esl['religion_name'] = esl['religion_name'].fillna(0).astype(np.int64)
esl.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 748 entries, 0 to 747
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Name        748 non-null    object
 1   birth_year  436 non-null    object
 2   death_year  466 non-null    object
 3   Target      748 non-null    object
 4   first_year  748 non-null    int64 
 5   last_year   748 non-null    int64 
dtypes: int64(2), object(4)
memory usage: 35.2+ KB
```

```
esl
```

	Name	birth_year	death_year	Target	first_year	last_year
0	William Adam	NaN	NaN	ESL	1844	1844
1	William (1) Adams	NaN	NaN	ESL	1844	1844
2	William (2) Adams	1,820	1,900	ESL	1858	1871
3	Louis Agassiz	1,807	1,873	ESL	1860	1871
4	Augustine Aglio	1,777	1,857	ESL	1843	1845
...	...	...	...	...	...	...
743	James Wyld	1,812	1,887	ESL	1844	1854
744	Ashton Yates	1,781	1,863	ESL	1860	1862
745	W Holt Yates	1,802	1,874	ESL	1844	1846
746	James Yearsley	1,805	1,869	ESL	1845	1845
747	Arthur de Zeltner	NaN	NaN	ESL	1865	1871

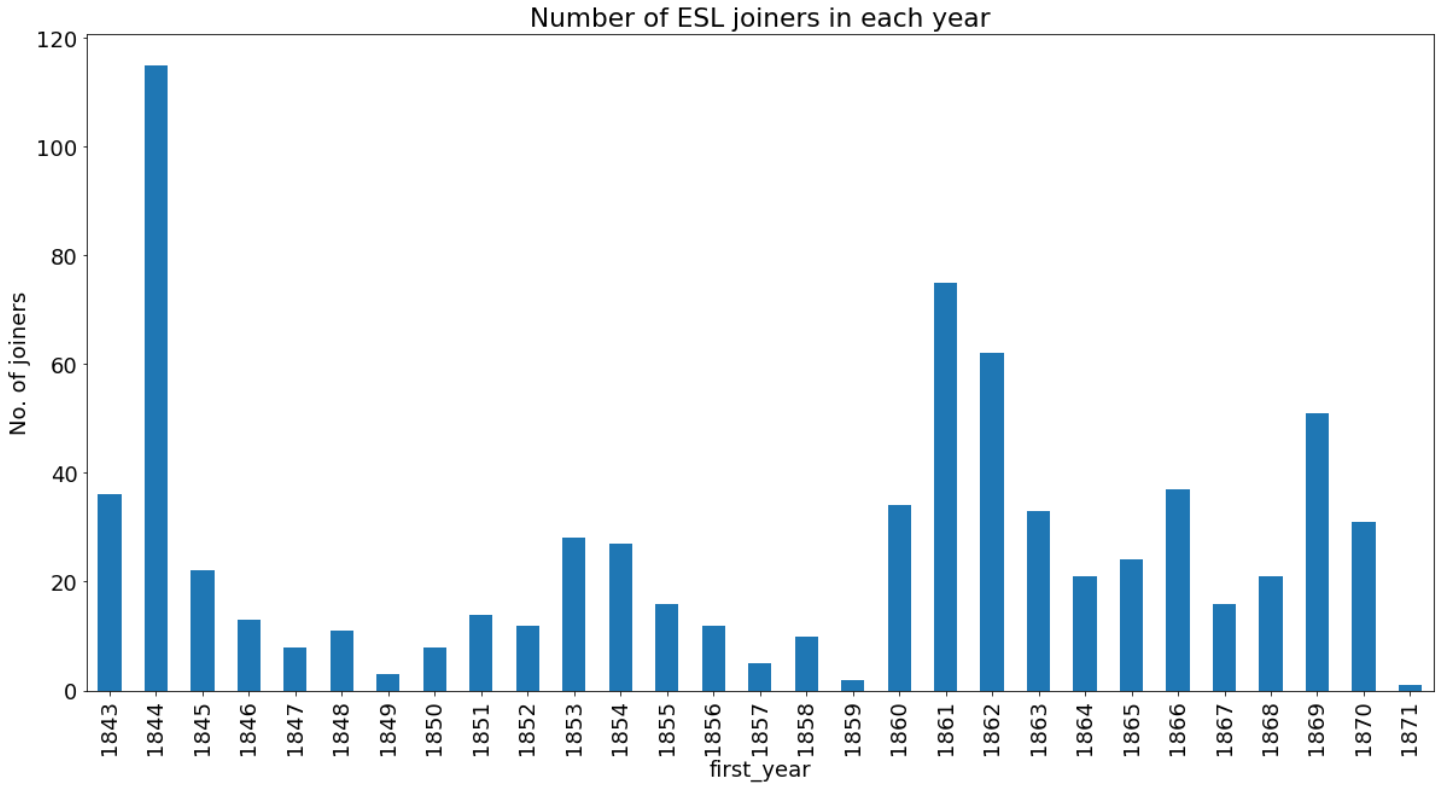
748 rows × 6 columns

```
quakers_esl = pd.read_csv ('vw_4_ceda_membership_quakers_esl2.csv')
quakers_esl
```

	Name	birth_year	death_year	religion_name	ceda_name	person_ceda_first
0	William Horton Lloyd	NaN	NaN	Quaker	ESL	
1	Joseph Lister	1827.0	1912.0	Quaker	ESL	
2	Thomas (1) Hodgkin	1798.0	1866.0	Quaker	ESL	
3	John Henry Gurney	1819.0	1890.0	Quaker	ESL	
4	Charles Henry Fox	NaN	NaN	Quaker	ESL	
5	William Fowler	NaN	NaN	Quaker	ESL	
6	Robert Nicholas Fowler	1828.0	1891.0	Quaker	ESL	
7	David Dale	1829.0	1906.0	Quaker	ESL	
8	x Collier	NaN	NaN	Quaker	ESL	
9	William Clay	1791.0	1869.0	Quaker	ESL	
10	Henry Christy	1810.0	1865.0	Quaker	ESL	
11	James Bell	1818.0	1872.0	Quaker	ESL	
12	James (1) Backhouse	1794.0	1869.0	Quaker	ESL	
13	Edward Backhouse	1808.0	1879.0	Quaker	ESL	
14	William Aldam	1813.0	1890.0	Quaker	ESL	

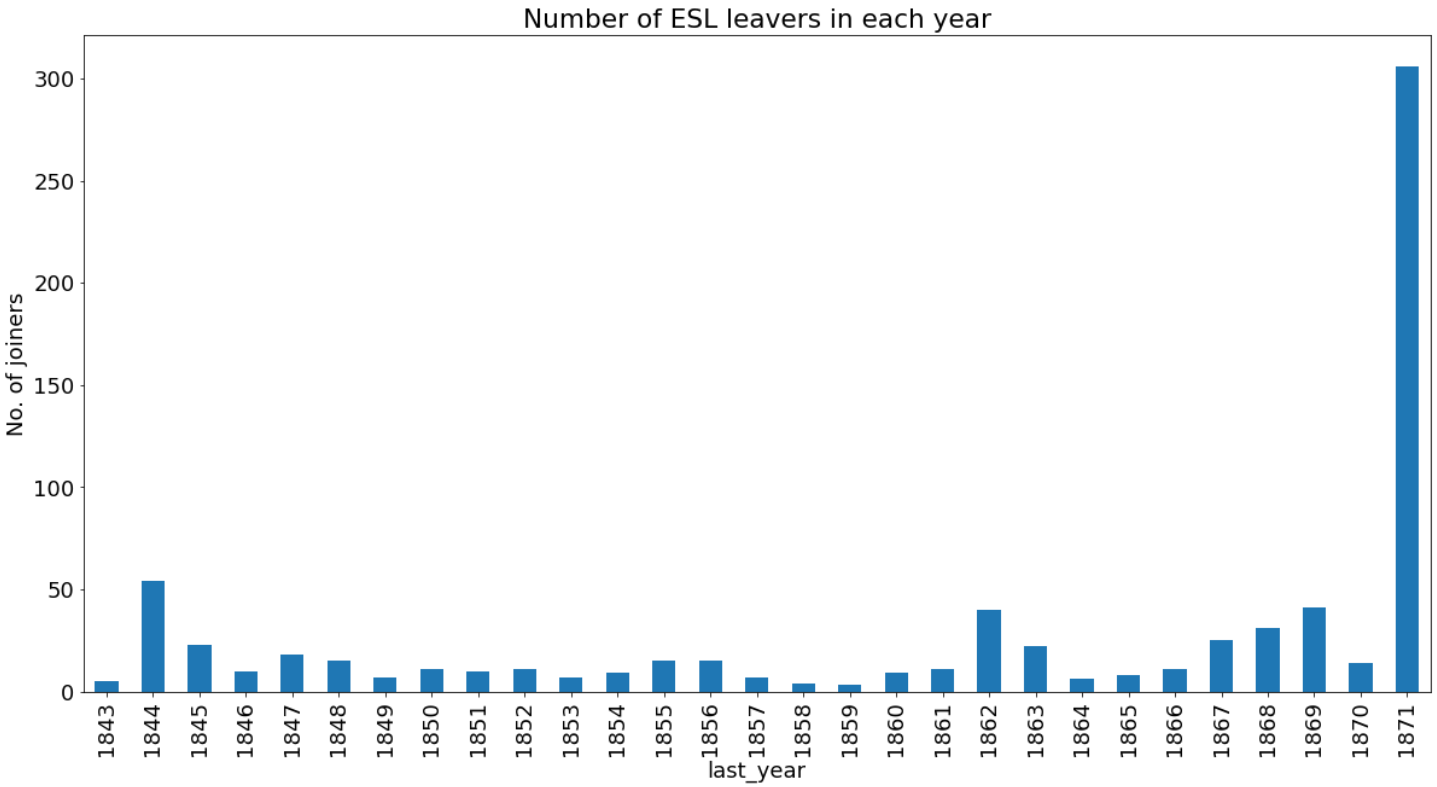
4.13 ESL joiners in each year

```
esl.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of ESL joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



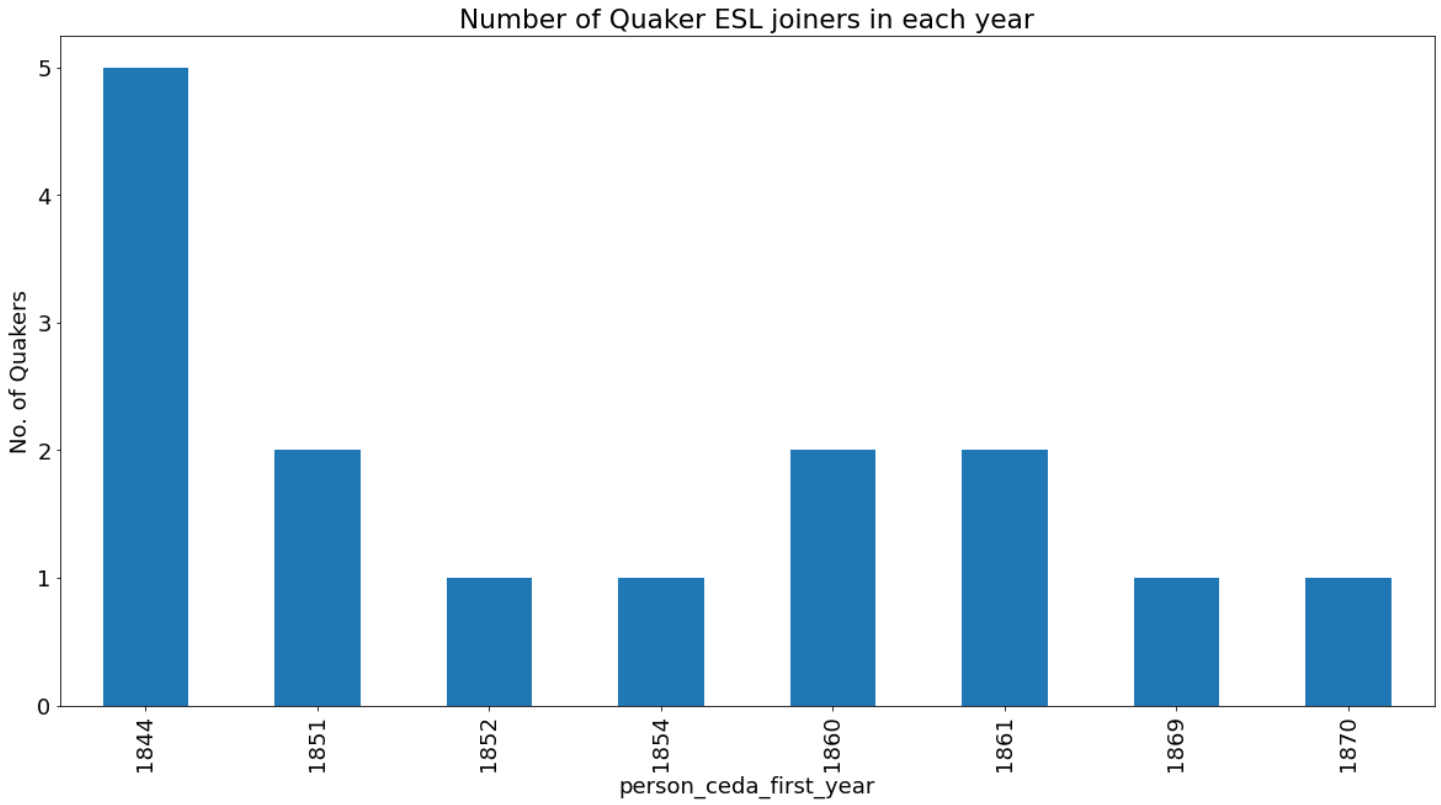
4.14 ESL leavers in each year

```
esl.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of ESL leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



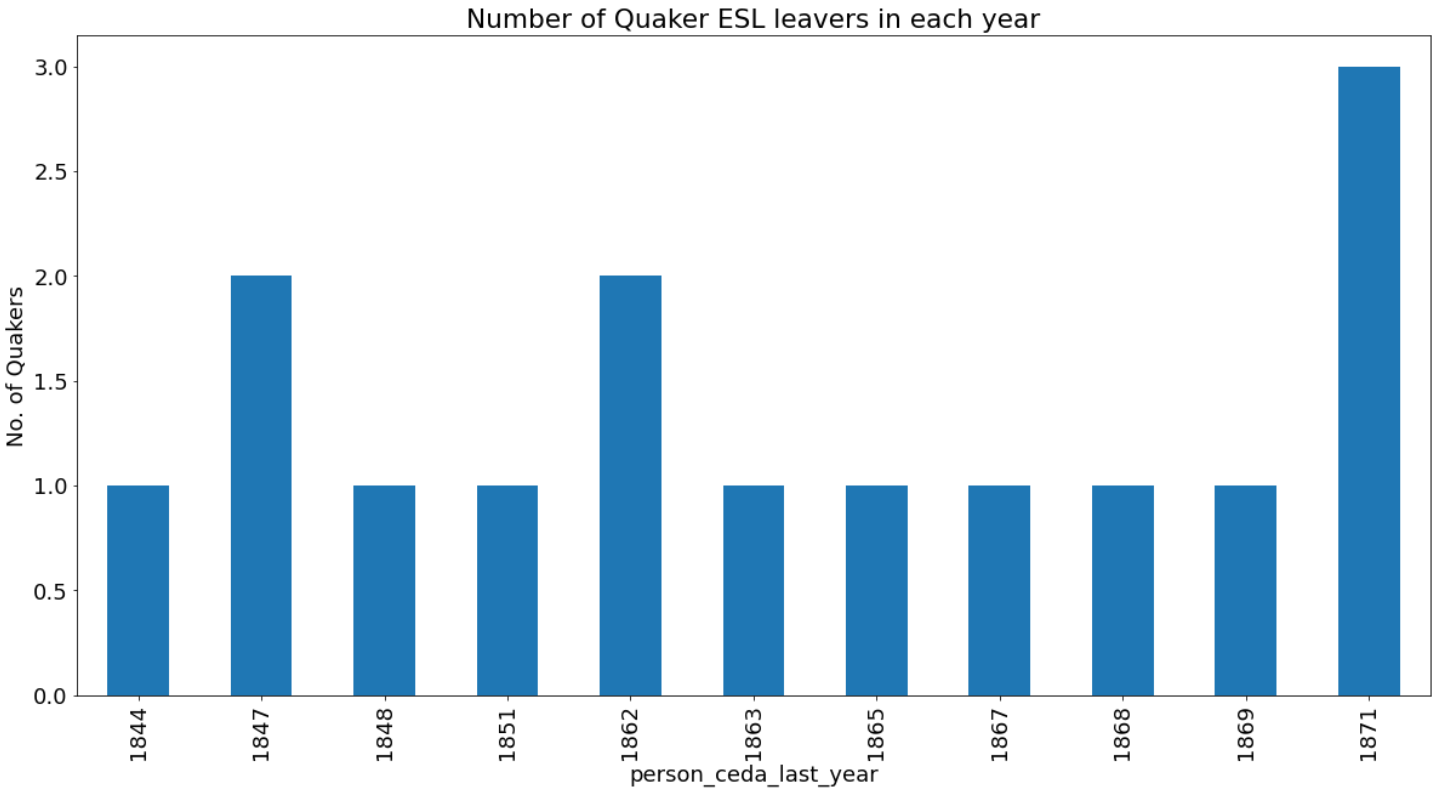
4.15 ESL Quaker joiners in each year

```
quakers_esl.groupby('person_ceda_first_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker ESL joiners in each year")
plt.ylabel ("No. of Quakers")
plt.show()
```



4.16 ESL Quaker leavers in each year

```
quakers_esl.groupby('person_ceda_last_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker ESL leavers in each year")
plt.ylabel ("No. of Quakers")
plt.show()
```



4.17 The Anthropological Society of London (ASL) 1863 - 1871

```
asl = pd.read_csv ('vw_4_ceda_membership_dates_asl.csv')
asl['birth_year'] = asl ['birth_year'].fillna(0).astype(np.int64)
asl['death_year'] = asl['death_year'].fillna(0).astype(np.int64)
```

```
asl.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1334 entries, 0 to 1333
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Name        1334 non-null   object
 1   birth_year  1334 non-null   int64 
 2   death_year  1334 non-null   int64 
 3   Target      1334 non-null   object
 4   first_year  1334 non-null   int64 
 5   last_year   1334 non-null   int64 
dtypes: int64(4), object(2)
memory usage: 62.7+ KB
```

```
asl
```

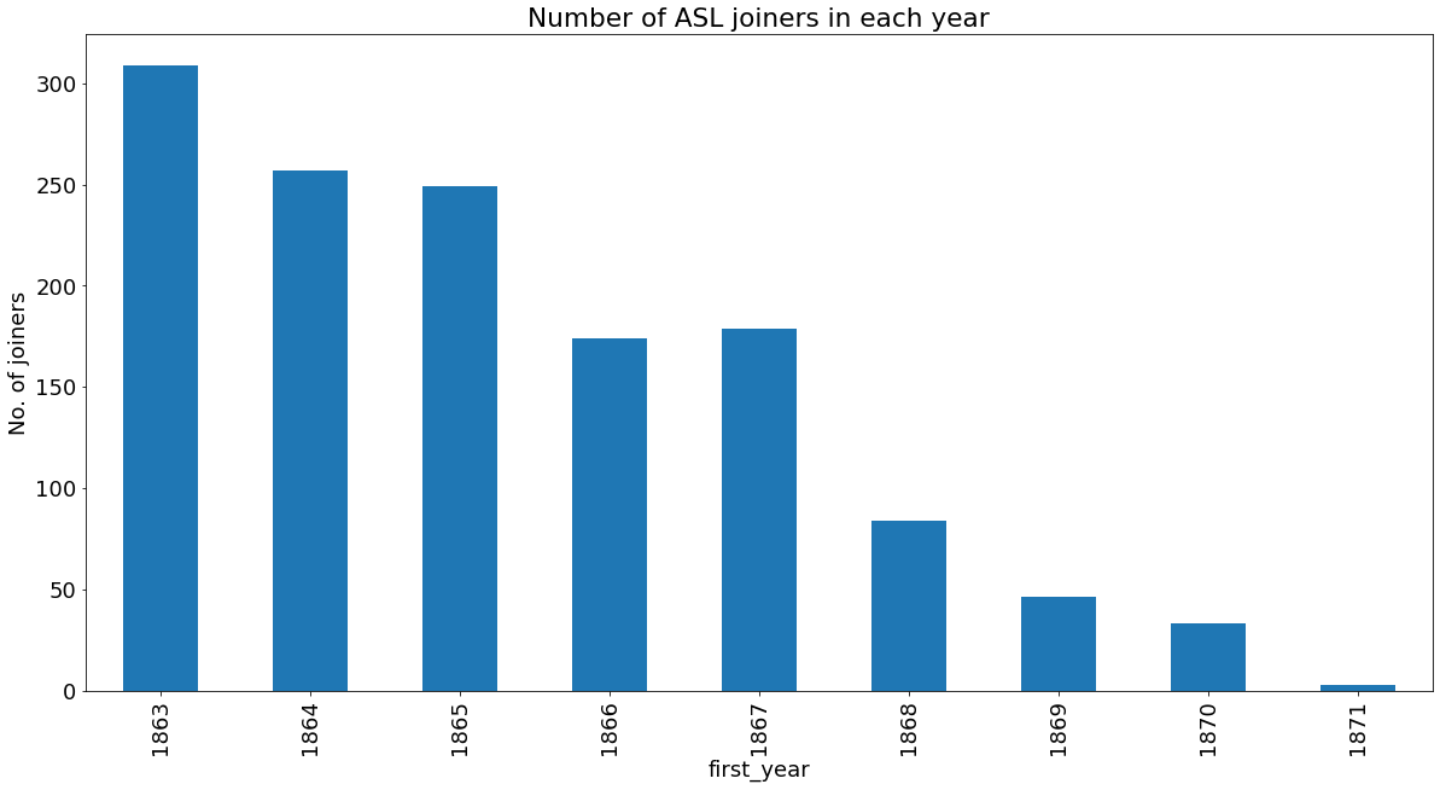
	Name	birth_year	death_year	Target	first_year	last_year
0	Arthur William A Beckett	1844	1909	ASL	1864	1867
1	Andrew Mercer Adam	0	0	ASL	1865	1867
2	H R Adam	0	0	ASL	1870	1871
3	Henry John Adams	0	0	ASL	1864	1869
4	William Adlam	0	0	ASL	1863	1866
...	...	...	...	...	...	...
1329	Stephen Yeldham	1810	1896	ASL	1866	1869
1330	James A Youl	1811	1904	ASL	1864	1865
1331	Robert Younge	1801	1874	ASL	1865	1871
1332	Arthur de Zeltner	0	0	ASL	1866	1871
1333	x Zohrab	0	0	ASL	1867	1871

1334 rows × 6 columns

```
quakers_asl = pd.read_csv ('vw_4_ceda_membership_quakers_asl2.csv')
```

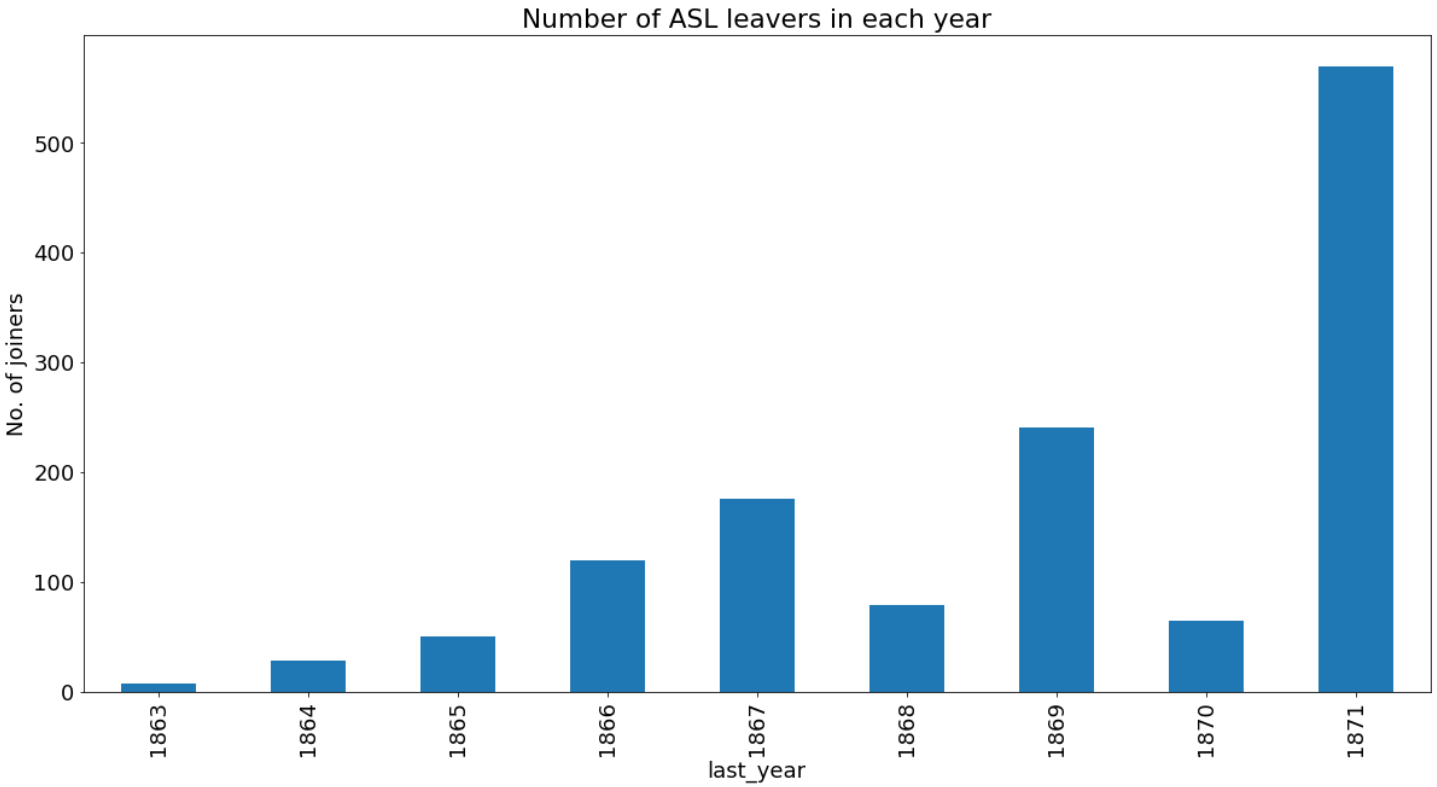
4.18 ASL joiners in each year

```
asl.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of ASL joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



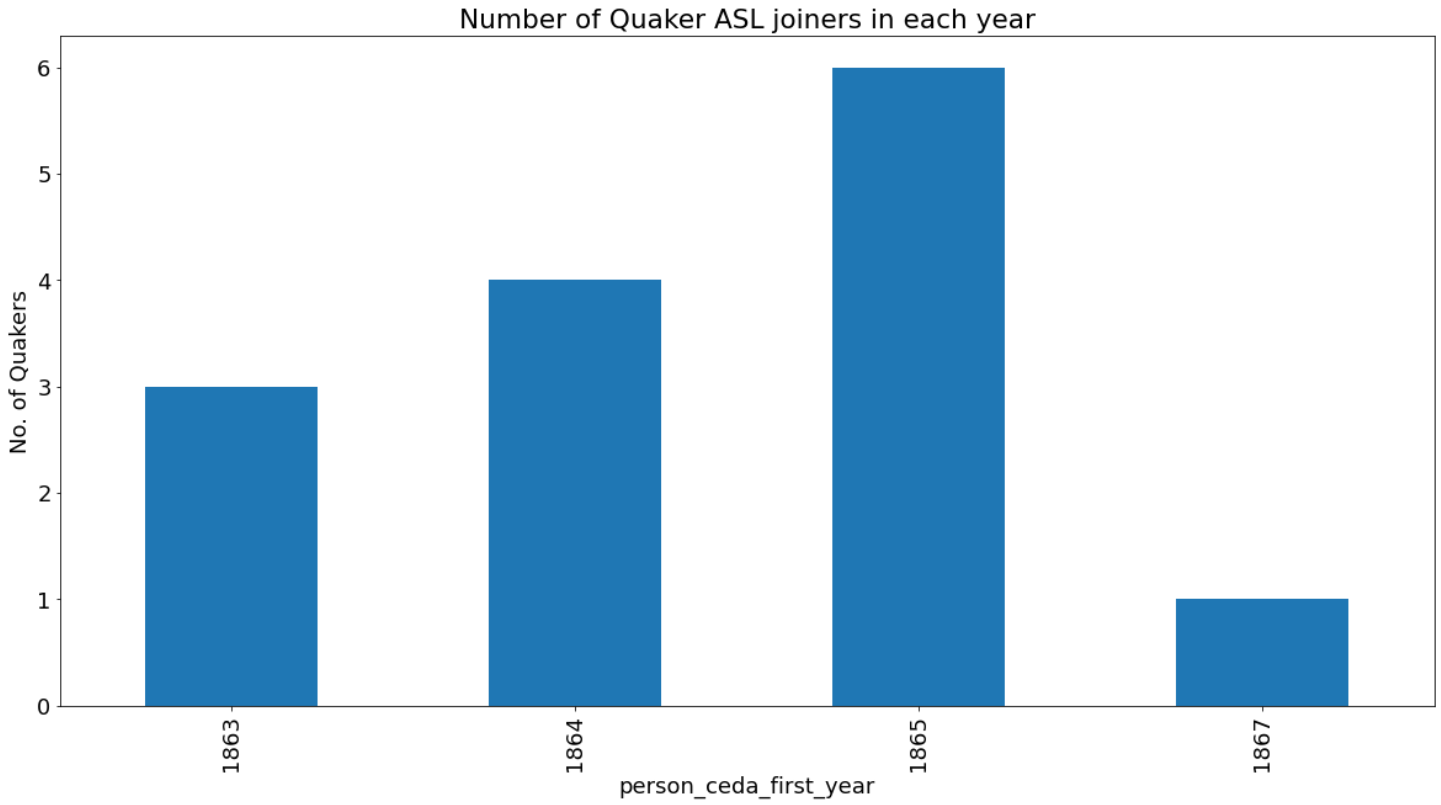
4.19 ASL leavers in each year

```
asl.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of ASL leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



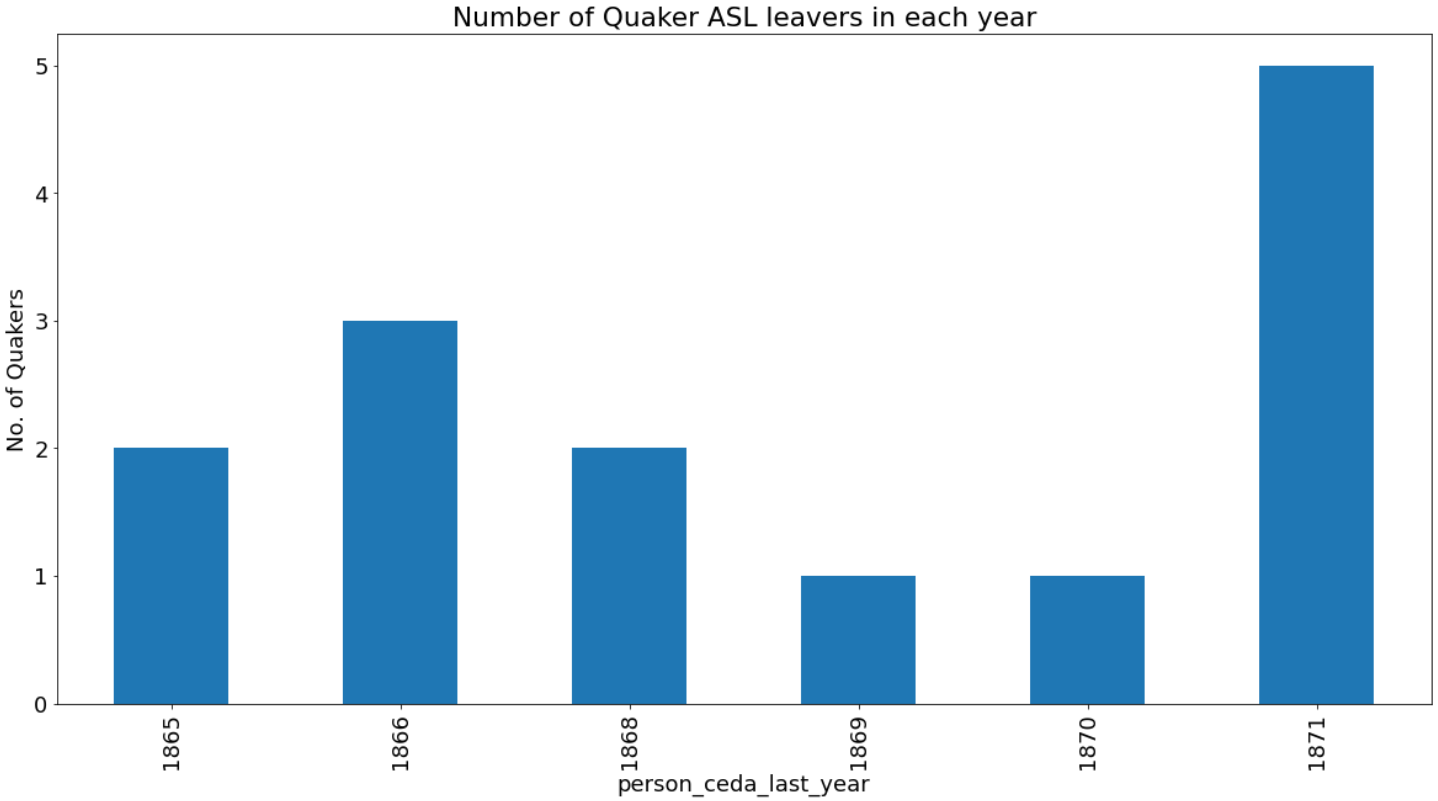
4.20 ASL Quaker joiners in each year

```
quakers_asl.groupby('person_ceda_first_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker ASL joiners in each year")
plt.ylabel ("No. of Quakers")
plt.show()
```



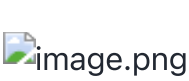
4.21 ASL Quaker leavers in each year

```
quakers_asl.groupby('person_ceda_last_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker ASL leavers in each year")
plt.ylabel ("No. of Quakers")
plt.show()
```




```
quakers_asl = pd.read_csv ('vw_4_ceda_membership_quakers_asl2.csv')
quakers_asl
```

	Name	birth_year	death_year	religion_name	ceda_name	person_ceda_firs
0	William Spicer Wood	NaN	1902.0	Quaker	ASL	
1	William Wilson	1785.0	1868.0	Quaker	ASL	
2	James Wilson	NaN	NaN	Quaker	ASL	
3	E T Wakefield	NaN	NaN	Quaker	ASL	
4	J Robinson	NaN	NaN	Quaker	ASL	
5	Jonathan Hutchinson	1828.0	1913.0	Quaker	ASL	
6	William Holmes	NaN	NaN	Quaker	ASL	
7	George Stacey Gibson	1818.0	1883.0	Quaker	ASL	
8	James T J Doyle	NaN	NaN	Quaker	ASL	
9	Henry Crowley	NaN	1887.0	Quaker	ASL	
10	Charles Buxton	1823.0	1871.0	Quaker	ASL	
11	William Bull	1828.0	1902.0	Quaker	ASL	
12	Antonio Brady	1811.0	1881.0	Quaker	ASL	
13	S Stafford Allen	1840.0	1870.0	Quaker	ASL	



4.22 Anthropological Institute (AI) 1843 - 1871

```
ai = pd.read_csv ('vw_4_ceda_membership_dates_ai.csv')
# code not needed for this set because in this datframe birth_year and death_year s
#ai['birth_year'] = ai ['birth_year'].fillna(0).astype(np.int64)
#ai['death_year'] = ai['death_year'].fillna(0).astype(np.int64)
```

```
ai.info ()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 610 entries, 0 to 609
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   Name        610 non-null    object
 1   birth_year  399 non-null    object
 2   death_year  436 non-null    object
 3   Target      610 non-null    object
 4   first_year  610 non-null    int64 
 5   last_year   610 non-null    int64 
dtypes: int64(2), object(4)
memory usage: 28.7+ KB
```

```
ai
```

	Name	birth_year	death_year	Target	first_year	last_year
0	H R Adam	NaN	NaN	AI	1870	1871
1	William (2) Adams	1,820	1,900	AI	1858	1871
2	Louis Agassiz	1,807	1,873	AI	1860	1871
3	Alexander Muirhead Aitken	NaN	NaN	AI	1864	1871
4	William Amhurst Tyssen Amhurst	1,835	1,909	AI	1862	1871
...	...	...	...	...	...	...
605	Robert Carr Woods	1,816	1,875	AI	1863	1871
606	Francis Beresford Wright	1,837	1,911	AI	1870	1871
607	Thomas Wright	1,810	1,877	AI	1853	1871
608	Robert Younge	1,801	1,874	AI	1865	1871
609	Arthur de Zeltner	NaN	NaN	AI	1865	1871

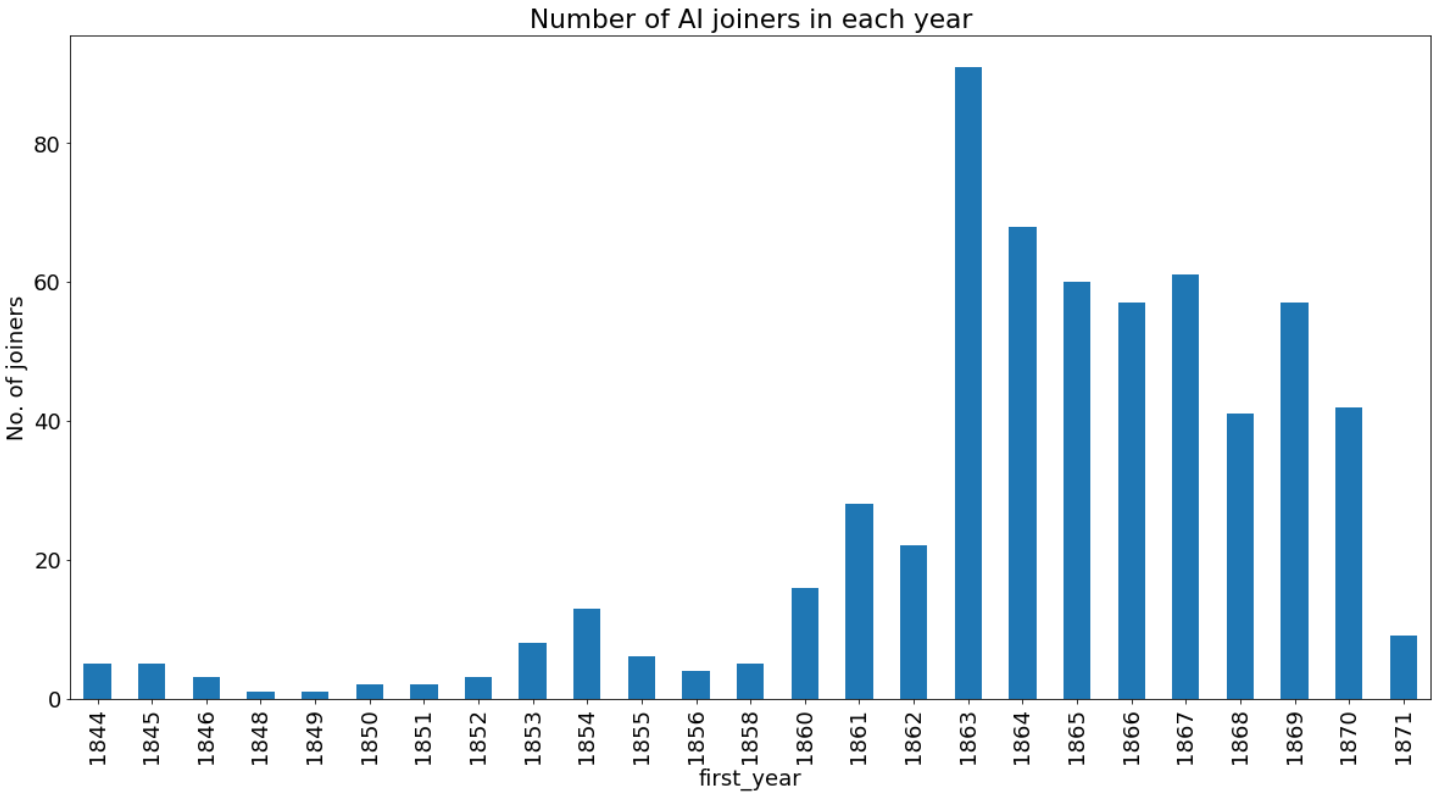
610 rows × 6 columns

```
quakers_ai = pd.read_csv ('vw_4_ceda_membership_quakers_ai2.csv')
quakers_ai
```

	Name	birth_year	death_year	religion_name	ceda_name	person_ceda_first_
0	William Spicer Wood	NaN	1902.0	Quaker	AI	
1	Jonathan Hutchinson	1828.0	1913.0	Quaker	AI	
2	Charles Henry Fox	NaN	NaN	Quaker	AI	
3	Robert Nicholas Fowler	1828.0	1891.0	Quaker	AI	
4	Henry Crowley	NaN	1887.0	Quaker	AI	
5	William Bull	1828.0	1902.0	Quaker	AI	
6	Antonio Brady	1811.0	1881.0	Quaker	AI	
7	Edward Backhouse	1808.0	1879.0	Quaker	AI	

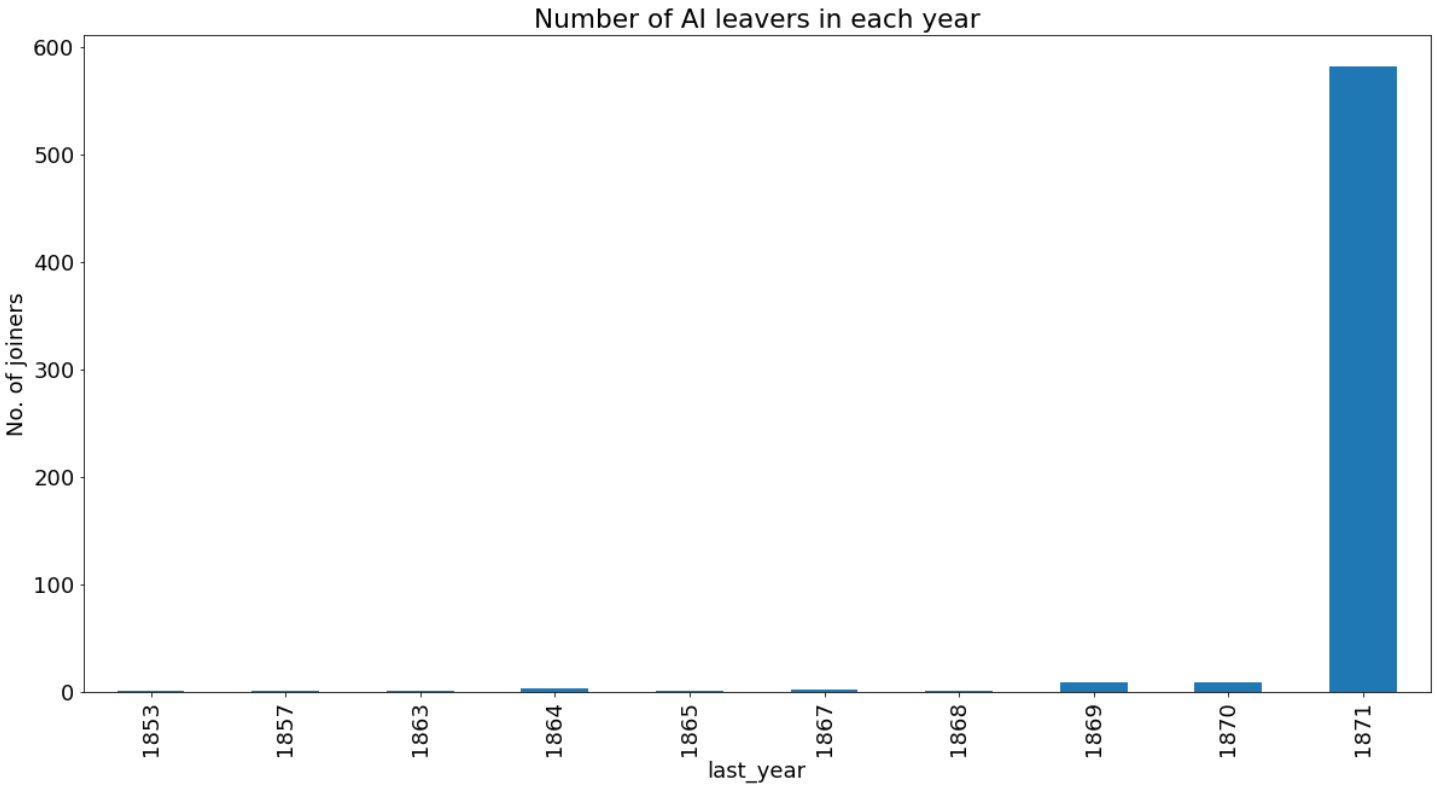
4.23 AI joiners in each year

```
ai.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of AI joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



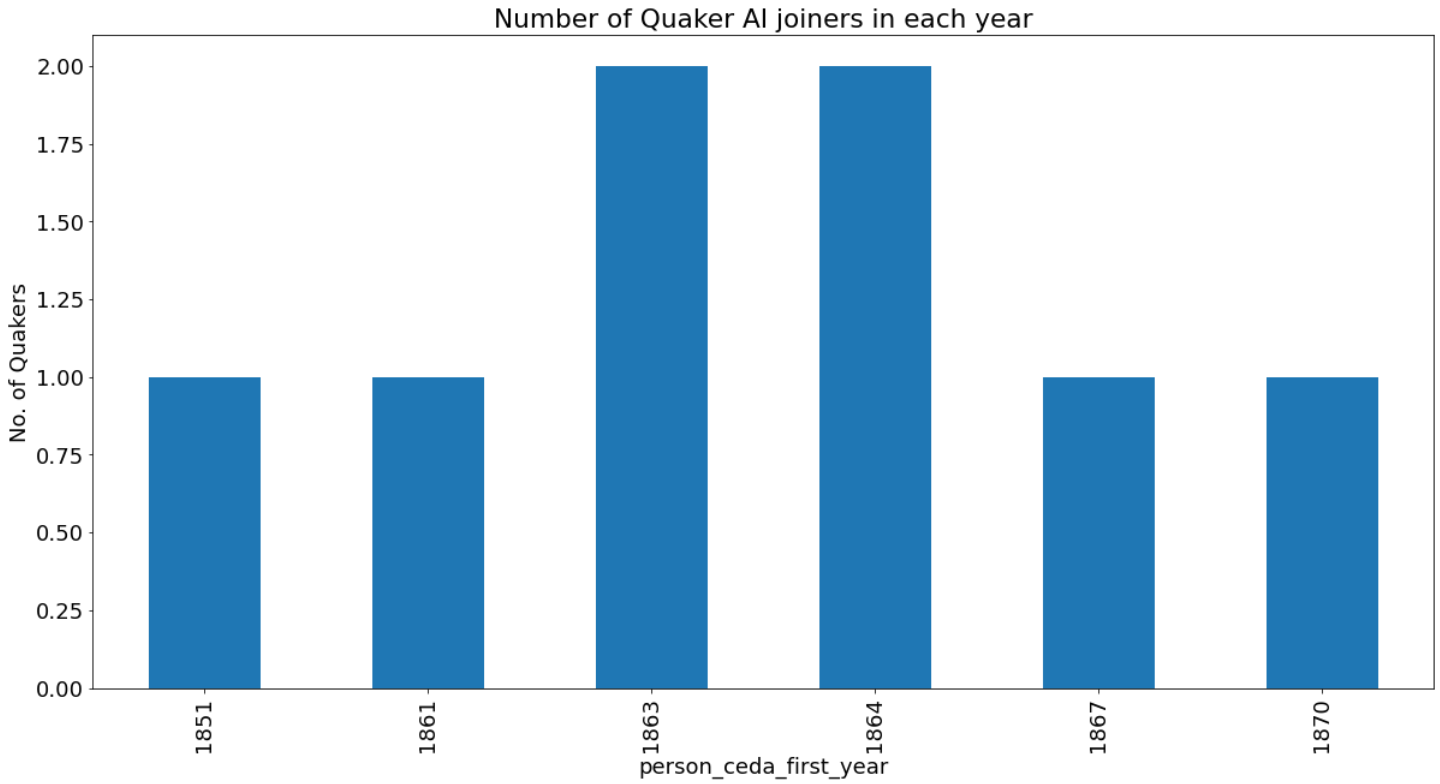
4.24 AI leavers in each year

```
ai.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of AI leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



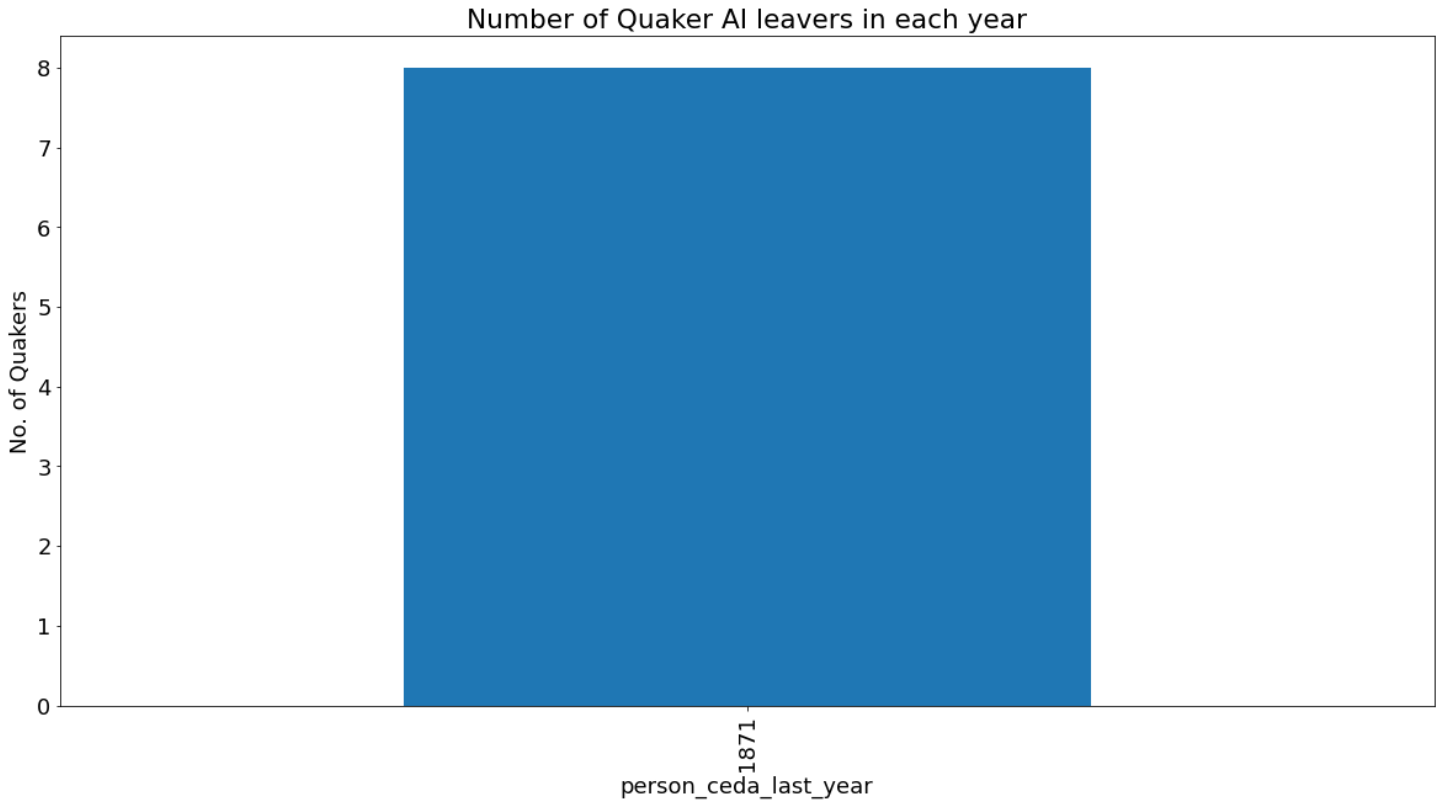
4.25 AI Quaker joiners in each year

```
quakers_ai.groupby('person_ceda_first_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker AI joiners in each year")
plt.ylabel ("No. of Quakers")
plt.show()
```



4.26 AI Quaker leavers in each year

```
quakers_ai.groupby('person_ceda_last_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker AI leavers in each year")
plt.ylabel ("No. of Quakers")
plt.show()
```



4.27 Duration of AI Quaker memberships

image.png

4.28 generate gexf output file of all CEDA data

for Gephi

```
with open('vw_1_person_with_quakers2.csv', 'r') as nodecsv: # Open the Nodes csv fi
    nodereader = csv.reader(nodecsv) # Read the csv
    nodes = [n for n in nodereader][1:]# Retrieve the data (using Python list compr
                                      # to remove the header row
    node_names = [n[0] for n in nodes] # Get a list of only the node names

with open('vw_hddt_ceda_tuples_attributes2.csv', 'r') as edgecsv: # Open the file
    edgereader = csv.reader(edgecsv) # Read the csv
    edge_list = list(edgereader) # Convert to list, so can iterate below in for loo

    # Create empty arrays to store edge data and edge attribute data
    edges = []
    edges_attributes = []

    # Fill the arrays with data from CSV
    for e in edge_list[1:]:
        edges.append(tuple(e[0:2])) # Get the first 2 columns (source, target) and
        edges_attributes.append(tuple(e[2:4])) # Get the 3rd and 4th columns (first

edge_names = [e[0] for e in edges] # Get a list of only the edge names
```

```
print("Nodes length: ", len(node_names))
print("Edges length: ", len(edges))
print("Edges attributes length: ", len(edges_attributes)) # This should be the same
```

```
Nodes length:  3094
Edges length:  4046
Edges attributes length:  4046
```

```
print("First 5 nodes:", node_names[0:5])
print("First 5 edges:", edges[0:5])
print("First 5 edges attributes:", edges_attributes[0:5])

# The output will appear below this code cell.
```

```
First 5 nodes: ['Arthur William A Beckett', 'Andrew Mercer Adam', 'H R Adam', 'Will
First 5 edges: [('William Adam', 'ESL'), ('William (1) Adams', 'ESL'), ('William (2
First 5 edges attributes: [('1844', '1844'), ('1844', '1844'), ('1858', '1871'), ('
```

```
G = nx.Graph()
G.add_nodes_from(node_names)
G.add_edges_from(edges)
print(nx.info(G))
```

```
Name:
Type: Graph
Number of nodes: 3100
Number of edges: 4021
Average degree:   2.5942
```

```
# Nodes

birth_year_dict = {}
death_year_dict = {}
religion_id_dict = {}

# Edges
first_year_dict = {}
last_year_dict = {}
```

```
for node in nodes: # Loop through the list, one row at a time

    birth_year_dict [node[0]] = node[1]
    death_year_dict [node[0]] = node[2]
    religion_id_dict[node[0]] = node[3]
```

```
for i, edge in enumerate(edges): # Loop through the list, one row at a time
    first_year_dict [(edge[0], edge[1])] = edges_attributes[i][0]
    last_year_dict [(edge[0], edge[1])] = edges_attributes[i][1]
```

```
# print(religion_id_dict)# list Source, target and first_year (all records). This s
# print(len(religion_id_dict))# At the end of the file print a count of all first_y
# print (religion_id_dict)
```

```
# Nodes
nx.set_node_attributes(G, birth_year_dict, 'birth_year')
nx.set_node_attributes(G, death_year_dict, 'death_year')
nx.set_node_attributes(G, religion_id_dict, 'religion_id')

# Edges
nx.set_edge_attributes(G, first_year_dict, 'first_year')
nx.set_edge_attributes(G, last_year_dict, 'last_year')
```

```
#for n in G.nodes(): # Loop through every node, in our data "n" will be the name of
#print(n, G.nodes[n]['birth_year']) # Access every node by its name, and then by th
```

```
nx.write_gexf(G, 'ceda_all_data_dyn_edges.gexf')
```

P7 Chapter 5a Thomas Hodgkin MD's networks - Part one

Chapter 6 Section 6.22

file_name: jnb_hddt_laidlaw

5.1 Protecting the Empire's Humanity: Thomas Hodgkin and British Colonial Activism 1830 - 1870 (Zoë Laidlaw 2021)

This 'HDDT - JNB' exercise analyses the persons listed in the index to Protecting the Empire's Humanity (Laidlaw 2021), (PEH), and correspondence received by and correspondence sent to Thomas Hodgkin MD 1799 - 1861, in the indexes to the Wellcome Inst., Hodgkin Family Archives. Selected persons from both archives are then compared with the CEDA database persons. The relationship between the three datasets is then examined to determine the extent to which the networks overlap or fit together; if a Hodgkin political activist network, then emerges, how central is that network to the activism of the wider CEDA network and do insights emerge that might indicate who the key influencers in the network might be?

5.2 GitHub

Make a private GitHub repository for the exercise and clone it to the University of Birmingham secure server space allocated for this project. KelvinBeerJones/jnb_hddt_laidlaw cloned to: http://localhost:8888/tree/OneDrive -20University of Birmingham/HDDT/jnb_project_containers/jnb_hddt_laidlaw

5.3 Call up the python packages needed to perform the analysis

1. Pandas, numpy and pyplotlib, which we will use to create tables and charts in the Workbook.
2. Plot.rc to specify the dimensions for all imported images (this keeps images to a uniform size and shape).
3. Itemgetter, NetworkX and nbconvert to create a Gexf file for Gephi, which is used to generate visualisation graph files and to enable visual analysis of the social networks to take place.
4. A csv reader to extract the selected sqlite database data from the curated views.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.rc('figure', figsize=(20, 10))
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('png', 'pdf')
from operator import itemgetter
import networkx as nx
from networkx.algorithms import community

#This part of networkx,
# for community detection, needs to be imported separately.
import nbconvert
import csv

# <img src="xxxx.png">
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[1], line 3
      1 import pandas as pd
      2 import numpy as np
----> 3 import matplotlib.pyplot as plt
      4 plt.rc('figure', figsize=(20, 10))
      5 from IPython.display import set_matplotlib_formats

ModuleNotFoundError: No module named 'matplotlib'
```

5.4 Call up the csv files from the SQL db and

prepare data for Gephi

```
# produce a 'names' file of nodes and a 'tuples' file of edges_attributes
# to generate the files need to produce GefX files for Gephi.

person_names = pd.read_csv ('vw_hddt_person_table.csv')

person_data_source = pd.read_csv ('vw_hddt_person_with_data_source.csv')

# Use these csv files in the 'with open' statements below
# to generate locations.gexf

names = pd.read_csv ('vw_hddt_person_name.csv')# For nodes csv
tuples = pd.read_csv ('vw_hddt_ceda_tuples.csv')# For edges.csv

with open('vw_hddt_person_name.csv', 'r') as nodecsv:

# Open the Nodes csv file
    nodereader = csv.reader(nodecsv)

# Read the csv
    nodes = [n for n in nodereader][1:]

# Retrieve the data (using Python list comprhension and list slicing
# to remove the header row

    node_names = [n[0] for n in nodes]

# Get a list of only the node names

with open('vw_hddt_ceda_tuples.csv', 'r') as edgecsv:

# Open the file

    edgereader = csv.reader(edgecsv)
# Read the csv

    edge_list = list(edgereader)

# Convert to list, so can iterate below in for loop

# Create empty arrays to store edge data and edge attribute data

edges = []
edges_attributes = []

# Fill the arrays with data from CSV

for e in edge_list[1:]:
    edges.append(tuple(e[0:2]))

# Get the first 2 columns (source, target) and add to array
# not used this time. edges_attributes.append(tuple(e[2:4]))
# Get the 3rd and 4th columns (first_year, last_year) and add to array
```

```
edge_names = [e[0] for e in edges] # Get a list of only the edge names
```

5.5 Introduction to the exercise - Part One

Laidlaw in the introduction to PEH sets out the importance of the social networks of Dr Thomas Hodgkin MD, “The roots of this book lie in the personal correspondence of the Quaker, scientist, and activist, Dr Thomas Hodgkin”, and “The exploration of Britain’s imperial history presented in this book is profoundly shaped by Thomas Hodgkin’s personal papers, today housed in the Wellcome library in London, and what they reveal of his philanthropic, medical, and scientific interests and networks. The volume and the breadth of that archive has allowed me to trace and assess a wide array of influences on “imperial humanitarianism” (2021, 3). Laidlaw also says that, Hodgkin’s personal archive at the Wellcome Institute constitutes The “backbone” of the book and that “Its study reveals 50 years’ worth of unlikely connections, sustained relationships, and closely argued, if sometimes contradictory, cases” (2021, 7).

Chapter 5 of the thesis argues that by only describing them in narratives it is difficult to ‘see’ the people who formed the extensive social networks in which Thomas Hodgkin MD operated, how many there were and how they relate to each other. And so, PEH, while discussing at length the efforts of Hodgkin’s social networks to relieve the plight of aborigines throughout the British Empire, does not make those networks visible or make them available to scrutiny. This Historical Data Analysis (HDA) fully addresses those two needs and presents new insights about Hodgkin’s networks that are difficult to achieve without an HDDT.

5.6 The 3094 members of the CEDA before the exercise

Before the Laidlaw exercise is performed, we can see in the Gephi graph the CEDA network using the Force Atlas algorithm. Far left and at the bottom we can see the QCA and those members of the QCA who led in the formation of the APS (which appears in purple). Two members of the QCA who join the APS also join with non QCA members of the APS in joining the ESL in 1843. These two are William Allen (who would die that year) and Thomas Hodgkin MD. In connecting up the QCA, the APS and the ESL these two stand out from the other members of the QCA, (half of whom go on to join the APS) but participate no further in network building. There is no discernible network

centered on Hodgkin alone. Thomas Hodgkin's personal network does not appear as a group node. The memberships of the ESL, the Anthropological Society of London (ASL) and Anthropological Institute (AI) are frequently shared. The ESL splits into two groups each of roughly equal size, those who are members of only the ESL and those members of the ESL who also share membership with the AI and ASL. The ASL (formed last in 1863) draws its membership from both the ESL and the AI. It is the ASL that will provide the bulk of the first memberships of the RAI. We can see 'ringed' the small groups of key influencers who network between the CEDA groups.

Society	abv.	Dates	Colour
Quaker Committee on the Aborigines*	QCA	1832/37 - 1846	Dark green
Aborigines Protection Society	APS	1837 - 1919	Purple
Ethnological Society of London	ESL	1843 - 1871	Blue
Anthropological Institute	AI	1843 - 1871	Orange
Anthropological Society of London	ASL	1863 - 1871	Green

5.7 Mods to db to facilitate this exercise - ZOE and WEL

(1) Persons in the index to PEH, and the members of the CEDA

All the person names were extracted from the PEH index (Laidlaw 2021, 359). Of the 290 person names in the index 108 were found to be already present in the HTTD CEDA dataset. The remaining 182 do not appear in the HDDT CEDA dataset, some of those indexed in PEH will not be members of Hodgkin's support network, but rather persons that Laidlaw has referenced in PEH for other reasons (for example King William IV, Queen Victoria, and many colonial officers of the Crown).

all persons PEH	PEH persons CEDA	PEH persons not CEDA
290	108	182

Note: At least 15 persons amongst the 182 non CEDA persons appearing in the index to PEH could be family members of persons already captured in the HDDT - from the awareness of the author of this thesis. Nonetheless the intention here is to discover how the 108 who are recorded in the HDDT database relate both to each other and the wider group of 3000 already in the HDDT, and to disregard the 182 who are not.

(2) Persons in the indexes to WEL, and the members of the CEDA

Because PEH relies heavily on the Hodgkin Family Archive at the Wellcome Institute an analysis of the two indexes to that collection was performed to extract from the index of letters sent and the index of letters received by Thomas Hodgkin MD those persons who appeared in both indexes indicating the these persons might have been members of Hodgkin's network.

In the Wellcome Hodgkin Family archive data indexes there are 107 person Hodgkin writes to and who also write to him, and of these 46 appear in the HDDT database and 61 do not. As in the PEH index exercise above we can reasonably assume both that some of these persons not already in the HDDT may be related to members of persons appearing in the HDDT database; and also, that many will not, for example we can expect to find many medical related correspondences in an archive collected by a medical history archive, and these are outside the scope of this thesis (which analyses political activism).

all persons WEL	WEL persons CEDA	WEL persons not CEDA
107	46	61

(3) Summary of db mods

Using the platform DBeaver (https://dbeaver.io/) the HDDT CEDA database was modified to accommodate the exercise:

1. We added to person_data_source table two new temporary data sources – ZOE and WEL
2. We added to ceda table two new CEDA groups – ZOE and WEL
3. Person_table. We uploaded 182 new records from a csv file of Laidlaw references, and allocated them to data_source = ZOE.
4. Person_table. We uploaded 61 new records from a csv file of Laidlaw references, and allocated them to data_source = WEL.
5. We updated m2m_person_ceda table to allocate 108 persons to a new CEDA group = ZOE
6. We updated m2m_person_ceda table to allocate 46 persons to a new CEDA group = WEL

Once the data from both ZOE and WEL had been added to the HDDT database the network analysis could be performed and a report in the form of a Jupyter Notebook made.

5.8 Assess persons in the index to PEH who are members of the CEDA.

The Index to PEH lists 108 persons who already present in the HDDT CEDA db. They were laidlaw allocated to a 'dummy' CEDA group (table CEDA, Target = 'ZOE'). This enables the visualisation of Laidlaw's Hodgkin network and shows its relationships to the original HDDT CEDA groups.

The indexes to WEL list 46 persons who are already present in the HDDT CEDA db. They were allocated to a 'dummy' CEDA group (table CEDA, Target = 'WEL'). This enables the visualisation of The Wellcome Inst., Hodgkin Family Archive Thomas Hodgkin MD network and shows its relationships to the original HDDT CEDA groups.

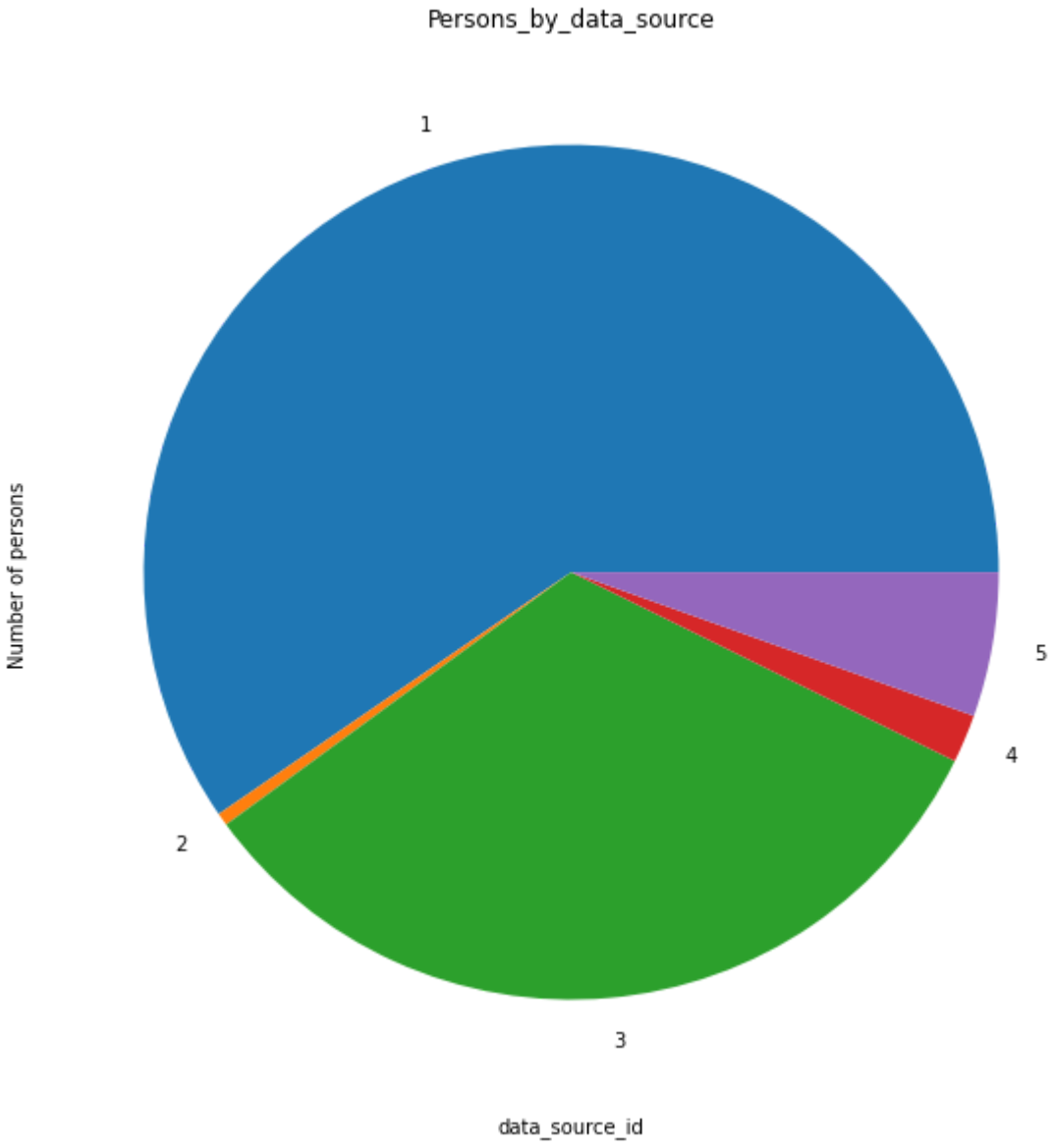
The 3337 persons in the CEDA db., make up 3892 memberships of the original CEDA (QCA, APS, ESL, AI, and the APS) The above 'new' CEDA were set up in the SQL db., to facilitate this exercise.

Original CEDA	ZOE	WEL	Total new
3892	108	46	4046

5.9 CEDA members compared to non-CEDA

others in PEH index

```
person_names.groupby('data_source_id')['Name'].nunique().plot(kind='pie')
plt.title ("Persons_by_data_source")
plt.xlabel ("data_source_id")
plt.ylabel ("Number of persons")
plt.show()
```



data_source_id	Source
1	RAI
2	QCA
3	APS
4	WEL
5	ZOE

The persons from PEH Index and the Welcome Inst., indexes who are not members of a CEDA appear here. They are disregarded in this exercise because they do not indicate the presence of a social network. They are shown here only for completeness.

Add 182 'ZOE' and 61 'WEL' Non CEDA persons to the SQL db., 'temporarily' solely to visualise the extent of persons not included in this exercise.

5.10 Data verification

In each of Code cells 4 - 11 We call up the tables we have obtained from the db to view the data. We can confirm (e.g., Code cell 4) that we have selected the correct table or view from the db., and we check that the first 5 and last 5 records have been rendered correctly. We can confirm (e.g. Code cell 5) that the respective table dataframe is formatted as expected. We also check that the number of records equals the number of rows on the data source csv.

Code cell 4

```
person_names
```

	Name	title	gender_id	birth_year	death_year	data_source_id
0	Arthur William A Beckett	NaN	1.0	1844.0	1909.0	1
1	Andrew Mercer Adam	NaN	1.0	NaN	NaN	1
2	H R Adam	NaN	1.0	NaN	NaN	1
3	William Adam	NaN	1.0	NaN	NaN	1
4	Henry John Adams	NaN	1.0	NaN	NaN	1
...	...	...	...	...	...	...
3332	James Wetherall	NaN	NaN	NaN	NaN	5
3333	William Wilberforce	NaN	NaN	NaN	NaN	5
3334	King William IV	NaN	NaN	NaN	NaN	5
3335	x Wiremu Kingi Te rangitake	NaN	NaN	NaN	NaN	5
3336	Johann Wohlers	NaN	NaN	NaN	NaN	5

3337 rows × 6 columns

Code cell 5

```
person_names.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3337 entries, 0 to 3336
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Name            3337 non-null   object 
 1   title           776 non-null    object 
 2   gender_id       1988 non-null   float64
 3   birth_year      1003 non-null   float64
 4   death_year      1069 non-null   float64
 5   data_source_id  3337 non-null   int64  
dtypes: float64(3), int64(1), object(2)
memory usage: 156.5+ KB
```

Code cell 6

```
person_data_source
```

	Name	data_source
0	Arthur William A Beckett	RAI
1	Andrew Mercer Adam	RAI
2	H R Adam	RAI
3	William Adam	RAI
4	Henry John Adams	RAI
...	...	...
3332	James Wetherall	ZOE
3333	William Wilberforce	ZOE
3334	King William IV	ZOE
3335	x Wiremu Kingi Te rangitake	ZOE
3336	Johann Wohlers	ZOE

3337 rows × 2 columns

Code cell 7

```
person_data_source.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3337 entries, 0 to 3336
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Name         3337 non-null   object
 1   data_source  3337 non-null   object
dtypes: object(2)
memory usage: 52.3+ KB
```

Code cell 8

```
names
```

	Name
0	Arthur William A Beckett
1	Andrew Mercer Adam
2	H R Adam
3	William Adam
4	Henry John Adams
...	...
3332	James Wetherall
3333	William Wilberforce
3334	King William IV
3335	x Wiremu Kingi Te rangitake
3336	Johann Wohlers

3337 rows × 1 columns

Code cell 9

```
names.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3337 entries, 0 to 3336
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Name    3337 non-null   object
dtypes: object(1)
memory usage: 26.2+ KB
```

Code cell 10

```
tuples
```

	Source	Target
0	William Adam	ESL
1	William (1) Adams	ESL
2	William (2) Adams	ESL
3	Louis Agassiz	ESL
4	Augustine Aglio	ESL
...	...	...
4041	Frederick Cooper	WEL
4042	Henry Christy	WEL
4043	James (1) Backhouse	WEL
4044	William (Capt.) Allen	WEL
4045	William (1) Adams	WEL

4046 rows × 2 columns

Code cell 11

```
tuples.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4046 entries, 0 to 4045
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Source  4046 non-null   object
 1   Target  4046 non-null   object
dtypes: object(2)
memory usage: 63.3+ KB
```

5.11 Generate gexf file for Gephi visualisation

Code cell 12 - 13 Check that Gephi 'Nodes' and 'Edges' files agree with 'names' and 'tuples' files

Code cell 12

```
print("Nodes length: ", len(node_names))
print("Edges length: ", len(edges))
```

```
Nodes length:  3337
Edges length:  4046
```

Code cell 13

```
print("First 5 nodes:", node_names[0:5])
print("First 5 edges:", edges[0:5])
```

```
First 5 nodes: ['Arthur William A Beckett', 'Andrew Mercer Adam', 'H R Adam', 'Will
First 5 edges: [('William Adam', 'ESL'), ('William (1) Adams', 'ESL'), ('William (2
```

Code cell 14 Execute NetworkX function

```
# We use NetworkX to build the graph data into a table

G = nx.Graph()
G.add_nodes_from(node_names)
G.add_edges_from(edges)
print(nx.info(G))
```

```
Name:
Type: Graph
Number of nodes: 3344
Number of edges: 4046
Average degree:   2.4199
```

The number of nodes here is 3337 persons plus 7 societies = 3344 (the additional 7 nodes are the CEDA names (CQA, APS, ESL, AI, ASL, ZOE and WEL). Gephi will produce a 'bigraph' of the selected data and a bigraph is a graph where relationships are between individual persons (one node) and membership organisations, many nodes).

Code cell 15 Write the gexf file

```
# Finally we can write a gexf file which will be placed in the root directory.
# We can then open the file in Gephi and visualize the network.

nx.write_gexf(G, 'ceda_laidlaw.gexf')
```

5.12 Visual analysis of the exercise

We then open the gexf file in Gephi and generate a graph file using the Force Atlas algorithm, the 'network diameter', 'modularity' routines and the 'appearance' routines to produce a suitable graph for analysis. (Running these routines in Gephi allows graph display and placement, colour and size

of nodes, modularity to identify clearly the large society groups and betweenness centrality to reveal individuals and the smaller groups who play important roles linking groups together. It should be noted that the visualisation and all of its topography are the result of running the above algorithms, it is not manually arranged on the page! Finally we save the graph in Gephi as a 'project file' to the JNB container for this exercise, and we also produce PNG files of the graph and selected areas. Finally we can import the png images of the Gephi graph file to this JNB to illustrate the network analysis performed in the Gephi platform.

5.13 The CEDA social network including ZOE and WEL

We have created two 'dummy' groups (ZOE and WEL) to show the persons who are members of the original CEDA and who appear in the index of PEH as Zoe, and those from the Wellcome Inst., as WEL. They appear in this graph in orange. Also in orange is the QCA group. It is helpful to show QCA alongside the two dummy groups because Thomas Hodgkin MD begins his political work in the QCA (as discussed in PEH), and all three groups are arguably Thomas Hodgkin MD groups. ZOE is centre, WEL to the right and QCA to the left. We can see that the dummy groups are centered in the Force Atlas graph and that they connect up all of the main CEDA groups. This is a visible confirmation that the Thomas Hodgkin MD network referenced in PEH is well placed and well connected. The presence of the dummy groups brings Thomas Hodgkin MD to the very centre of the graph, this is impressive given that the entire population is 3337 persons. But it is important to note that Hodgkin does not 'sit' within the community referenced by Laidlaw or that suggested by the WEL analysis, he sits to one side because as much as he is attracted to Laidlaw's and the WEL groups he is 'pulled' away from them because of his connections to the QCA and ESL.

Society	abv.	Dates	Colour
Quaker Committee on the Aborigines, Protecting the Empire's Humanity and Welcome Inst.,	QCA, PEH, WEL	1832/37 - 1846	Orange
Aborigines Protection Society	APS	1837 - 1919	Purple
Ethnological Society of London	ESL	1843 - 1871	Blue
Anthropological Society of London	ASL	1863 - 1871	Green
Anthropological Institute	AI	1843 - 1871	grey

Note: Gephi allows detailed examination of this network

5.14 Zooming in to show the network in detail

5.15 Other groupings emerge

Other smaller groups that liaise between Hodgkin and the CEDA also become visible in the graph, and these are worthy of further study.

5.16 Quaker roles emerge in detail

PEH also references 6 (of the 15) Quakers who were members of the QCA - Josiah and William Forster, Robert Howard, Peter Bedford, Joseph Sturge and Robert Alsop (Jun)and they can be seen here networking between the QCA, APS, ZOE and Thomas Hodgkin MD.

5.17 Conclusions

This exercise has shown that although Thomas Hodgkin's networks appear only in the index in PEH and in the Wellcome Inst., Hodgkin Archive, in neither of these sources can political activist relationships be easily deduced but, by using data analysis and data visualisation technology thenetworks argued in PEH can be shown and analysed very clearly.

The HDDT CEDA db., comprises the 3000 memberships of CEDA societies concerned firstly with the plight of aborigines, but then quickly afterwards with institution building in the science of ethnology and anthropology and within which Thomas Hodgkin was a key influencer. Placing PEH's Hodgkin networks alongside the HDDT networks, a much fuller view of community's political activism is obtained, where the centrality of Hodgkin's networks to the work of all of the CEDA networks is evident. Clearly, Laidlaw in PEH has in referencing over 100 key networkers, identified those who have close working connections with Hodgkin, and these networks are central to the workings of the greater networks of the CEDA. Other smaller embedded networking groups that liaise between Hodgkin and the CEDA have also been revealed, and these are worthy of further detailed study.

Although PEH offers a literary description of the networks of Hodgkin, Hodgkin himself does not get subsumed by the Gephi graph algorithms into ZOE or WEL, instead he stands aside. This is because, as we can see, his relationships with Quakers and the APS are strong enough to resist the attraction of his relationships with ZOE or WEL networks. This finding is important because it gives good reason to examine Hodgkin's relationships further with both QCA and the APS (and the ESL). Six Quakers who are key networkers between Hodgkin's concern for the plight of aborigines and his institution building in the science of anthropology also can be identified and their presence will help to shape the next exercise.

Chapter 6 will thoroughly explore the role of Quakers and chapter 7 the role of Hodgkin's networks supporting institution building in ethnology and anthropology within the APS and the ESL.

The exercise confirms and supports the centrality and importance of Hodgkin's networks as set out in the index to PEH and invites further scrutiny of those networks because key individuals and small clusters of persons emerge from the visual analysis.

5.18 Modifications to the database for Part Two

The ‘dummy’ groups ZOE and WEL, after being scrutinised using a Gephi graph file, add richness and insight into the workings of the CEDA networks and the role of Thomas Hodgkin within those networks. The role of Quakers within these networks is also indicated. Because the new data in ZOE and WEL does not include visual anomalies or reveal a large number of outlying persons (who would add no value to a study of person-to-person networks) we can be confident in now modifying the CEDA database permanently by merging them both into a new CEDA group called HOD. This part of the exercise will be performed in Chapter 5 Part Two.

5.19 Github upload

We can now update GitHub to pass the exercise and all its resources to the project repo (see step 1) . This enables the entire exercise to be both scrutinised by others and replicated elsewhere. (When the exercise is completed and audited, and all copyright issue resolved the repo can be made public).

End of laidlaw (part one)

P7 Chapter 5b Thomas Hodgkin’s MD networks - Part two

Chapter 6 Section 6.22 Case Study 3: Thomas Hodgkin’s MD networks

File name: jnb_hddt_laidlaw2

Protecting the Empire's Humanity (PEH): Thomas Hodgkin and British Colonial Activism 1830 - 1870 (Zoë Laidlaw 2021)

5.20 Preparation

In Part Two of the exercise we modify the HDDT database to accept the data extracted from PEH and WEL, labelling it as a new CEDA called 'HOD' to show Thomas Hodgkin MD's personal network. (note: This is his political network that Laidlaw observed in archival research as primarily supporting Hodgkin's work to relieve the plight of Aborigines. It does not include his 'medical' or 'scientific' networks.)

5.21 Github

Make a private GitHub repository for the exercise and clone it to the University of Birmingham secure server space allocated for this project. KelvinBeerJones/jnb_laidlaw2 cloned to this container

5.22 Call up the python packages needed to perform the analysis

1. Pandas, numpy and pyplotlib, - used to create tables and charts in the Workbook.
2. Plot.rc - to specify the dimensions for all imported images (this keeps images to a uniform size and shape).
3. Itemgetter, NetworkX and nbconvert - to create a Gexf file for Gephi, which is used to generate visualisations and to perform visual analysis of the social networks.
4. csv reader - to extract the selected sqlite database data from the selected db., views.

```
# First we call up the python packages we need to perform the analysis:

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.rc('figure', figsize=(20, 10))
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('png', 'pdf')
from operator import itemgetter
import networkx as nx
from networkx.algorithms import community

#This part of networkx,
# for community detection, needs to be imported separately.
import nbconvert
import csv

# <img src="xxxx.png">
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[1], line 5
      3 import pandas as pd
      4 import numpy as np
----> 5 import matplotlib.pyplot as plt
      6 plt.rc('figure', figsize=(20, 10))
      7 from IPython.display import set_matplotlib_formats

ModuleNotFoundError: No module named 'matplotlib'
```

5.23 call up the csv files and prepare data for

Gephi visualisation

```
person_names = pd.read_csv ('vw_hddt_person_table2.csv')
hod = pd.read_csv ('laidlaw_hod.csv')

names2 = pd.read_csv ('vw_hddt_person_name2.csv')# For nodes csv
tuples2 = pd.read_csv ('vw_hddt_ceda_tuples2.csv')# For edges.csv

with open('vw_hddt_person_name2.csv', 'r') as nodecsv:

# Open the Nodes csv file
    nodereader = csv.reader(nodecsv)

# Read the csv
    nodes = [n for n in nodereader][1:]

# Retrieve the data (using Python list comprhension and list slicing
# to remove the header row

    node_names = [n[0] for n in nodes]

# Get a list of only the node names

with open('vw_hddt_ceda_tuples2.csv', 'r') as edgecsv:

# Open the file

    edgereader = csv.reader(edgecsv)
# Read the csv

    edge_list = list(edgereader)

# Convert to list, so can iterate below in for loop

# Create empty arrays to store edge data and edge attribute data

edges = []
edges_attributes = []

# Fill the arrays with data from CSV

for e in edge_list[1:]:
    edges.append(tuple(e[0:2]))

# Get the first 2 columns (source, target) and add to array
# not used this time. edges_attributes.append(tuple(e[2:4]))
# Get the 3rd and 4th columns (first_year, last_year) and add to array

edge_names = [e[0] for e in edges] # Get a list of only the edge names
```

5.24 Introduction to the exercise - Part Two

As a result of the exercise performed in Laidlaw (Part One) we accept that a new CEDA can be created called HOD to represent the personal political network of Thomas Hodgkin MD as extracted from the Index to PEH and the indexes to the Wellcome Inst., Hodgkin Family Archive. All of the members of this new CEDA are also already recorded in the HTTD database as members of at least one of the original CEDA. In this part of the exercise we amend the HTTD database to include the CEDA group HOD.

Laidlaw's research into the Wellcome Inst., Hodgkin Collection reveals an important and relevant social network amongst the HDDT CEDA persons – based on Laidlaw's close study of Thomas Hodgkin's personal correspondence (where the receiver of correspondence also writes to him). We select some of Laidlaw's person references because they already appear in the HDDT CEDA database, and they complement the data initially collected for this thesis because they provide new information about existing HDDT persons and networking.

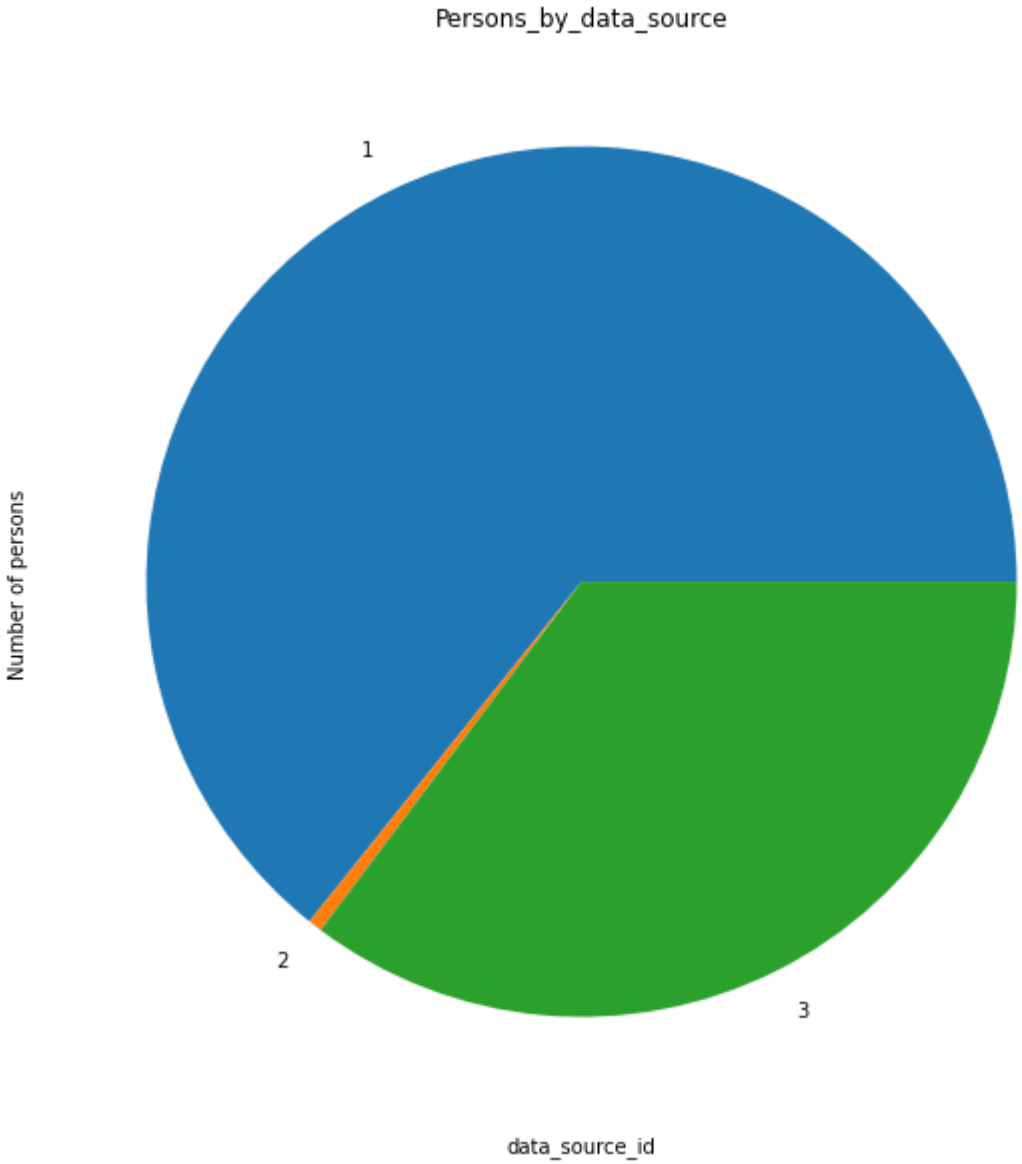
This necessitates amendments to the SQLite database and the production of another (this) Jupyter Notebook made to examine and verify the deepened HDDT CEDA networking in the HDDT as a whole after the Laidlaw HOD modifications had been made.

5.25 Data verification

The members of the Centres for the Emergence of the Discipline of Anthropology in Britain (CEDA) after accepting the new Laidlaw Exercise (Part One) data assigning persons to a new CEDA called HOD. We show that the data_sources 'WEL' and 'ZOE' used in Laidlaw Exercise (part One) have been removed from the database. (They were temporarily placed in the HDDT solely as 'dummies' to show the number of persons referenced in PEH and WEL with two way correspondence, but disregarded by the Laidlaw (Part One) exercise because these person are not present in the original CEDA).

5.26 Person table after modification

```
person_names.groupby('data_source_id')['Name'].nunique().plot(kind='pie')
plt.title ("Persons_by_data_source")
plt.xlabel ("data_source_id")
plt.ylabel ("Number of persons")
plt.show()
```



data_source_id	Source
1	RAI
2	QCA
3	APS

Code cell 22 - Person table data

```
person_names
```

	Name	title	gender_id	birth_year	death_year	data_source_id	notes
0	Arthur William A Beckett	NaN	1.0	1844.0	1909.0	1	17 King Street, S. James's, S.W. 88 St James's...
1	Andrew Mercer Adam	NaN	1.0	NaN	NaN	1	Boston, Lincolnshire
2	H R Adam	NaN	1.0	NaN	NaN	1	Old Calabar, W. Africa
3	William Adam	NaN	1.0	NaN	NaN	1	NaN
4	Henry John Adams	NaN	1.0	NaN	NaN	1	14 Thornhill Square, N.
...	...	...	...	...	...	...	...
3089	x Wright	Rev Dr	NaN	NaN	NaN	3	NaN
3090	W Wrigley	NaN	NaN	NaN	NaN	3	NaN
3091	James Yates	Rev	NaN	NaN	NaN	3	NaN
3092	John Young	NaN	NaN	NaN	NaN	3	NaN
3093	Thomas Zachary	NaN	NaN	NaN	NaN	3	NaN

3094 rows × 7 columns

5.27 Persons who are members of the new HOD CEDA

```
hod
```

	person_id	Name	birth_year	death_year	Target
0	3386	John Washington	NaN	NaN	HOD
1	3371	Jan Tzatzoe	NaN	NaN	HOD
2	3366	J H Tredgold	NaN	NaN	HOD
3	3359	H B Thorpe	NaN	NaN	HOD
4	3357	Perronet Thompson	NaN	NaN	HOD
...	...	...	...	...	...
149	465	Frederick Cooper	NaN	NaN	HOD
150	403	Henry Christy	1,810	1,865	HOD
151	81	James (1) Backhouse	1,794	1,869	HOD
152	28	William (Capt.) Allen	NaN	NaN	HOD
153	7	William (1) Adams	NaN	NaN	HOD

154 rows × 5 columns

5.28 Generate gexf file for Gephi visualisation

Code cell 24 - Check volume of data for Gephi visualisation graph

```
print("Nodes length: ", len(node_names))
print("Edges length: ", len(edges))

# not used this time.
print("Edges attributes length: ", len(edges_attributes))

# This should be the same length as edges
```

```
Nodes length:  3094
Edges length:  4046
Edges attributes length:  0
```

Code cell 25 - Check the data quality for Gephi visualisation graph

```
# First check that the data is correctly formatted

print("First 5 nodes:", node_names[0:5])
print("First 5 edges:", edges[0:5])
# not used this time. print("First 5 edges attributes:", edges_attributes[0:5])

# The output will appear below this code cell.
```

```
First 5 nodes: ['Arthur William A Beckett', 'Andrew Mercer Adam', 'H R Adam', 'Will
First 5 edges: [('William Adam', 'ESL'), ('William (1) Adams', 'ESL'), ('William (2
```

Code cell 26 - NetworkX function

```
# We use NetworkX to build the graph data into a table

G = nx.Graph()
G.add_nodes_from(node_names)
G.add_edges_from(edges)
print(nx.info(G))
```

```
Name:
Type: Graph
Number of nodes: 3100
Number of edges: 4021
Average degree:   2.5942
```

The number of nodes here is 3094 persons plus 6 groups = 3100 (the additional 6 nodes are the CEDA names (CQA, APS, ESL, AI, ASL, and HOD). Gephi will produce a ‘bigraph’ of the data where relationships are beween individual persons and membership organisations.

Code cell 27 - Write the gexf file

```
# Finally we can write a gexf file which will be placed in the root directory.
# We can then open the file in Gephi and visualize the network.

nx.write_gexf(G, 'ceda_laidlaw2.gexf')
```

5.29 Visual analysis of the exercise

5.30 The CEDA political network with HOD added

Society	abv.	Dates	Colour
Quaker Committee on the Aborigines and the Thomas Hodgkin MD group	QCA	1832/37 - 1846	Dark green
Aborigines Protection Society	APS	1837 - 1919	Purple
Ethnological Society of London	ESL	1843 - 1871	Blue
Anthropological Society of London	ASL	1863 - 1871	Light Green
Anthropological Institute	AI	1843 - 1871	Orange
Protecting the Empire's Humanity	HOD	2021	dark green

The Hodgkin network and it's relationships (shown above) are much clearer now that the groups WEL and ZOE have been combined into one. (Both of these former groups were identified by Laidlaw in PEH). The graph is best read 'right' to 'left' following the groups shown in dark green. The Quaker Committee on the Aborigines (QCA), active from 1832 - 1837 (or 1846?) appears top

right. This group is ‘led’ by Thomas Hodgkin MD. Below is the APS formed in 1837 and active to 1919 (beyond the entire period studied in the thesis). We know that Thomas Hodgkin MD formed the APS at Ratcliffe Quaker Meeting House in 1837.

“Dr Hodgkin moved that an auxiliary society be formed in Ratcliff [? Quaker meeting ?] for the purpose of promoting the objects of the Aborigines Protection Society and more especially to collect information from persons recently arrived from abroad and to exert an interest in those who might be going out as colonists or sailors. He observed that though a great amount of valuable information relating to the subjects now under consideration was brought to this part from various parts of the globe very great difficulty had been experienced in collecting it. The formation of the proposed branch society might do much to overcome this difficulty.”

(WELLCOME LIBRARY FOR THE HISTORY AND UNDERSTANDING OF MEDICINE, DEPARTMENT OF ARCHIVES AND MANUSCRIPTS. HODGKIN FAMILY PAPERS 1996 PP/HO/D, Thomas Hodgkin MD (1798 1866), General Material on Civilisation and Colonialization. Aborigines Protection Society General Materials.)

PP/HO/D/D148, Minutes of the First Meeting, (3ff), 1837

Thomas Hodgkin’s network (HOD) does not centre closely to the QCA, it lies at the heart of the greater network collected and compiled in the HTTD. It links most strongly with the APS, but also has good connectivity with the ESL and later the ASL. It has poor connectivity to the AI.

5.31 The CEDA political network with HOD added in detail

We can see that Hodgkin sits apart, pulled (By the Force Atlas algorithm) to sit between the QCA, the APS and his own personal network (HOD). He is revealled as highly networked and this indicates a possible key influencer.

The next exercise (Chapter 6) will examine a much greater political activist network suporting and supported by Thomas Hodgkin MD, and one that is not revelaed in it’s full extent by this exercise, - Quakers in Britain.

5.32 Github upload

We can now update GitHub to pass this exercise and all its resources to the dedicated project repo (see step 1). This enables the entire exercise to be both scrutinised by others and replicated elsewhere (When the exercise is completed and audited, and all copyright issue resolved the repo can be made public).

P7 Chapter 6 Case Study 2 589 Quakers and their family relationships

Thesis Chapter 6 Section 6.21

File Name: jnb_hddt_quaker_tables

6.1 Import resources

```
import csv
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from operator import itemgetter
import networkx as nx
from networkx.algorithms import community
#This part of networkx, for community detection, needs to be imported separately.
import nbconvert
import seaborn as sns
plt.rc('figure', figsize=(20, 10))
# <img src=" xxx.png">
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[1], line 3
      1 import csv
      2 import pandas as pd
----> 3 import matplotlib.pyplot as plt
      4 import numpy as np
      5 from operator import itemgetter

ModuleNotFoundError: No module named 'matplotlib'
```

```
quakers = pd.read_csv ('vw_1_quakers.csv')
quakers['birth_year'] = quakers['death_year'].fillna(0).astype(np.int64)
quakers['death_year'] = quakers['death_year'].fillna(0).astype(np.int64)

quaker_relationships = pd.read_csv ('vw_5_person1_person2.csv')
immediate = pd.read_csv ('vw_5_quaker_relationships_3.csv')
close = pd.read_csv ('vw_5_quaker_relationships_2.csv')
distant = pd.read_csv ('vw_5_quaker_relationships_1.csv')

quaker_ceda = pd.read_csv('vw_4_ceda_membership_quakers2.csv')
quaker_aps = pd.read_csv ('vw_4_ceda_membership_quakers_aps2.csv')
quaker_esl = pd.read_csv('vw_4_ceda_membership_quakers_esl2.csv')
quaker_asl = pd.read_csv('vw_4_ceda_membership_quakers_asl2.csv')
quaker_ai = pd.read_csv('vw_4_ceda_membership_quakers_ai2.csv')
quaker_qca = pd.read_csv('vw_4_ceda_membership_quakers_qca2.csv')
quaker_hod = pd.read_csv('vw_4_ceda_membership_quakers_hod2.csv')
quaker_not_hod = pd.read_csv('vw_4_ceda_membership_quakers_not_hod2.csv')
```

Quakers with CEDA memberships but without family relationships are circled in blue

Quakers begin their engagement with the Quaker Committee on the Aborigines. Led by Thomas Hodgkin MD (who can be seen in the centre of the graph) they then become members of the Aborigines Protection Society where they comprise 50% of the members. Some Quakers then go on to be members of the Ethnological Society of London, the Anthropological Society of London, and finally the Anthropological Institute.

6.2 List out all Quakers in the database

```
quakers
```

	Name	birth_year	death_year	data_source_id
0	William Aldam	1890	1890	1
1	S Stafford Allen	1870	1870	1
2	Edward Backhouse	1879	1879	1
3	James (1) Backhouse	1869	1869	1
4	James Bell	1872	1872	1
...	...	...	...	...
584	Joshua Wilson	0	0	3
585	F Woodhead	0	0	3
586	W Woolston	0	0	3
587	Francis Wright	0	0	3
588	S W Wright	0	0	3

589 rows × 4 columns

6.3 List out all the Quaker family relationships

```
quaker_relationships
```

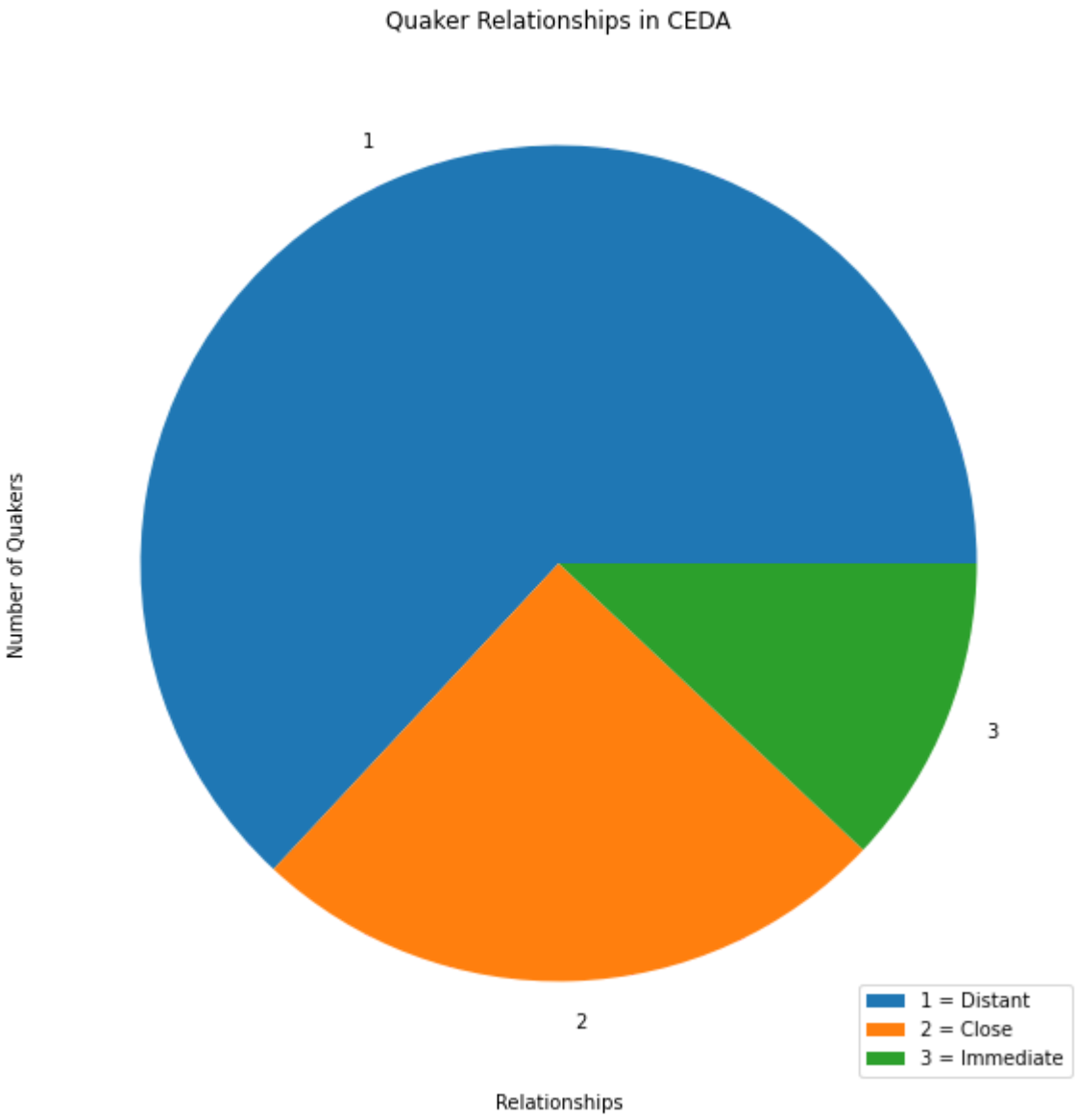
	Source	Target	relationship_type_id
0	William Aldam	x Fox	1
1	William Jun Aldam	x Fox	1
2	Frederick Alexander	R D Alexander	1
3	G W Alexander	R D Alexander	1
4	Henry Alexander	R D Alexander	1
...	...	...	...
2001	Alfred Waterhouse	R Waterhouse	3
2002	Mary Waterhouse	Paul Bevan	3

	Source	Target	relationship_type_id
2003	Lucy Westcombe	Thomas Westcombe	3
2004	Benjamin Wheeler	Samuel Wheeler	3
2005	Charles Wilson	Joshua Wilson	3

2006 rows × 3 columns

6.4 All Quaker family relationships

```
# quaker_relationships.groupby('relationship_type_id')['Source'].nunique().plot(kin
quaker_relationships.groupby('relationship_type_id')['Source'].count().plot(kind='p
plt.title ("Quaker Relationships in CEDA")
plt.xlabel ("Relationships")
plt.ylabel ("Number of Quakers")
plt.legend(["1 = Distant", "2 = Close", "3 = Immediate"], loc ="lower right")
plt.show()
```



6.5 Quakers and their family relationship networks

6.6 Immediate relationships

```
immediate
```

	Source	Target	relationship_type_id
0	Arthur Albright	John M Albright	3
1	Arthur Albright	Rachel Albright	3
2	Arthur Albright	William Albright	3
3	Rachel Albright	John M Albright	3
4	Rachel Albright	William Albright	3
...	...	...	...
236	Alfred Waterhouse	R Waterhouse	3
237	Mary Waterhouse	Paul Bevan	3
238	Lucy Westcombe	Thomas Westcombe	3
239	Benjamin Wheeler	Samuel Wheeler	3
240	Charles Wilson	Joshua Wilson	3

241 rows × 3 columns

6.7 Close relationships

```
close
```

	Source	Target	relationship_type_id
0	R D Alexander	Christopher Bowley	2
1	R D Alexander	Robert Charleton	2
2	R D Alexander	Frederick H Fox	2
3	R D Alexander	Thomas Maw	2
4	R D Alexander	William Norton	2
...	...	...	...
495	W Whiting	John Whiting	2
496	Isaac Wilson	S Braithwaite	2

	Source	Target	relationship_type_id
497	Isaac Wilson	John Jowett	2
498	Isaac Wilson	John E Wilson	2
499	William Spicer Wood	Daniel Doncaster	2

500 rows × 3 columns

6.8 Distant relationships

```
distant
```

	Source	Target	relationship_type_id
0	William Aldam	x Fox	1
1	William Jun Aldam	x Fox	1
2	Frederick Alexander	R D Alexander	1
3	G W Alexander	R D Alexander	1
4	Henry Alexander	R D Alexander	1
...	...	...	...
1260	William Wilson	Barnard Dickinson	1
1261	William Wilson	Frederick Fryer	1
1262	William Wilson	Benjamin Jowett (2)	1
1263	William Wilson	John Pease	1
1264	William Wilson	Joseph Pease	1

1265 rows × 3 columns

6.9 Significant personal networks - Thomas Hodgkin MD

6.10 Significant personal networks - John Hodgkin

6.11 Significant personal networks - Edward Backhouse

6.12 Significant personal networks - William Fowler

6.13 List out all Quaker members of the CEDA

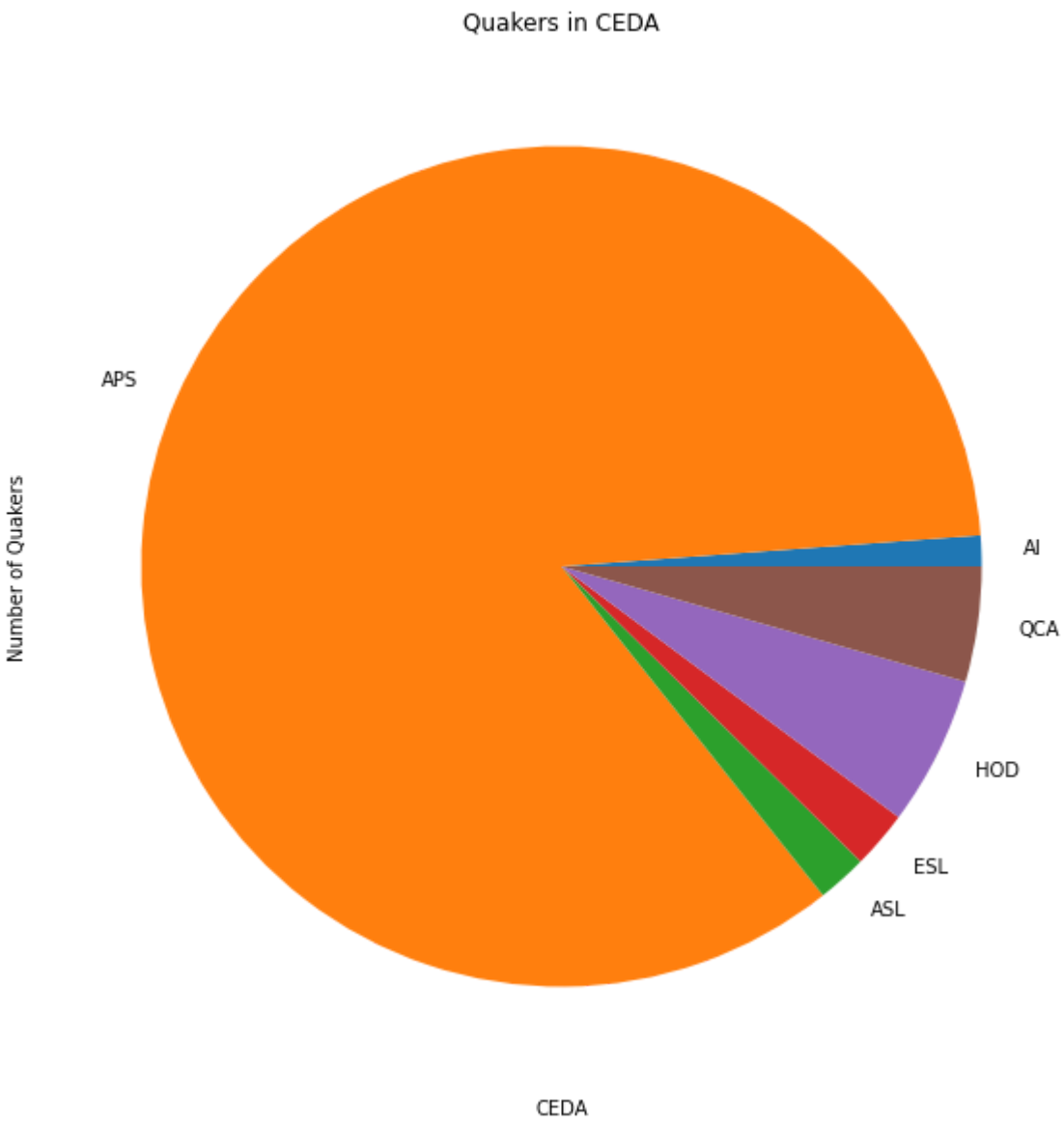
```
quaker_ceda
```

	Name	religion_name	ceda_name	first_year	last_year
0	William Spicer Wood	Quaker	APS	1864.0	1867.0
1	William Spicer Wood	Quaker	ASL	1863.0	1871.0
2	William Spicer Wood	Quaker	AI	1863.0	1871.0
3	William Wilson	Quaker	APS	1838.0	1865.0
4	William Wilson	Quaker	ASL	1865.0	1866.0
...	...	...	...	...	...
683	Joshua Wilson	Quaker	APS	1860.0	1860.0
684	F Woodhead	Quaker	APS	1861.0	1862.0
685	W Woolston	Quaker	APS	1861.0	1861.0
686	Francis Wright	Quaker	APS	1838.0	1838.0
687	S W Wright	Quaker	APS	1861.0	1861.0

688 rows × 5 columns

6.14 Pie chart Quaker CEDA memberships

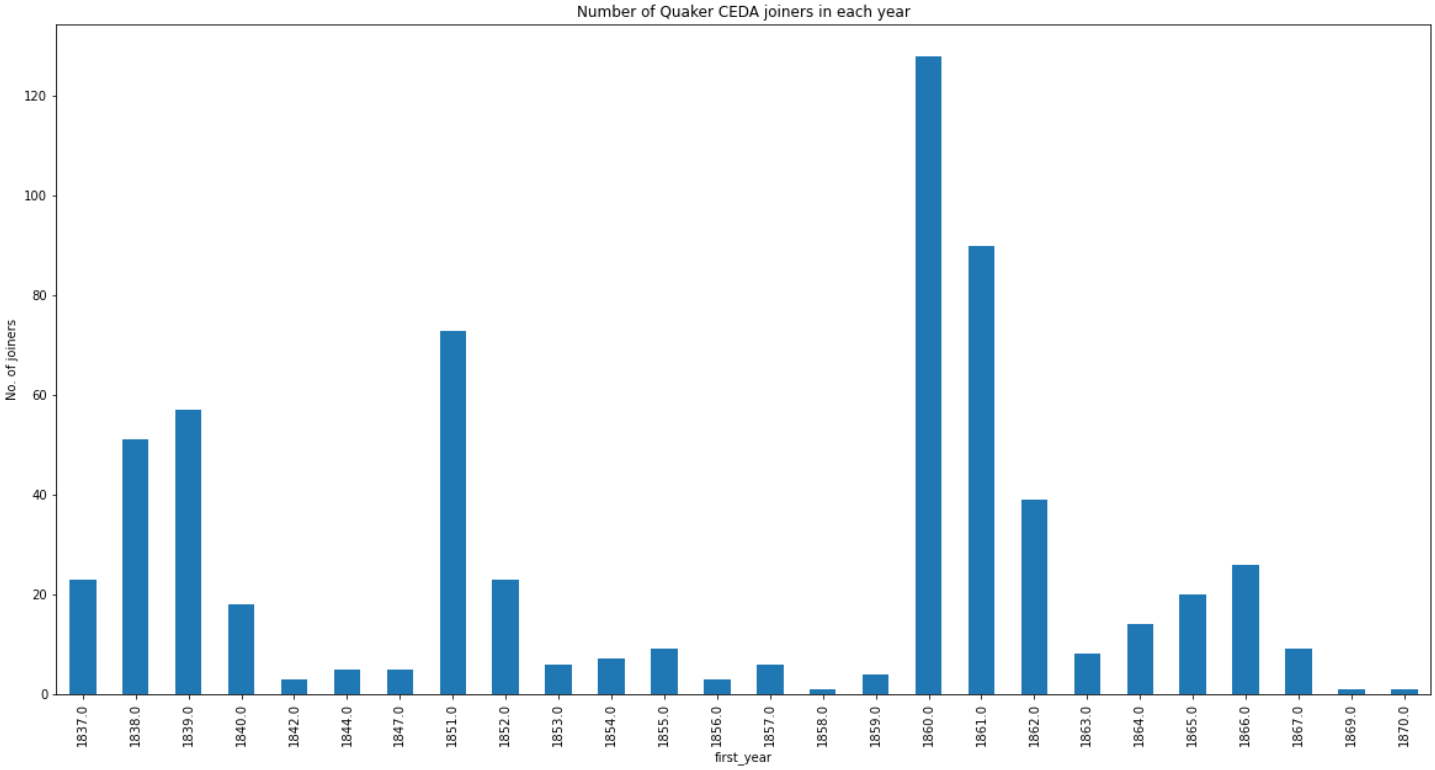
```
quaker_ceda.groupby('ceda_name')['Name'].nunique().plot(kind='pie')
plt.title ("Quakers in CEDA")
plt.xlabel ("CEDA")
plt.ylabel ("Number of Quakers")
plt.show()
```



6.15 Quaker CEDA membership networks

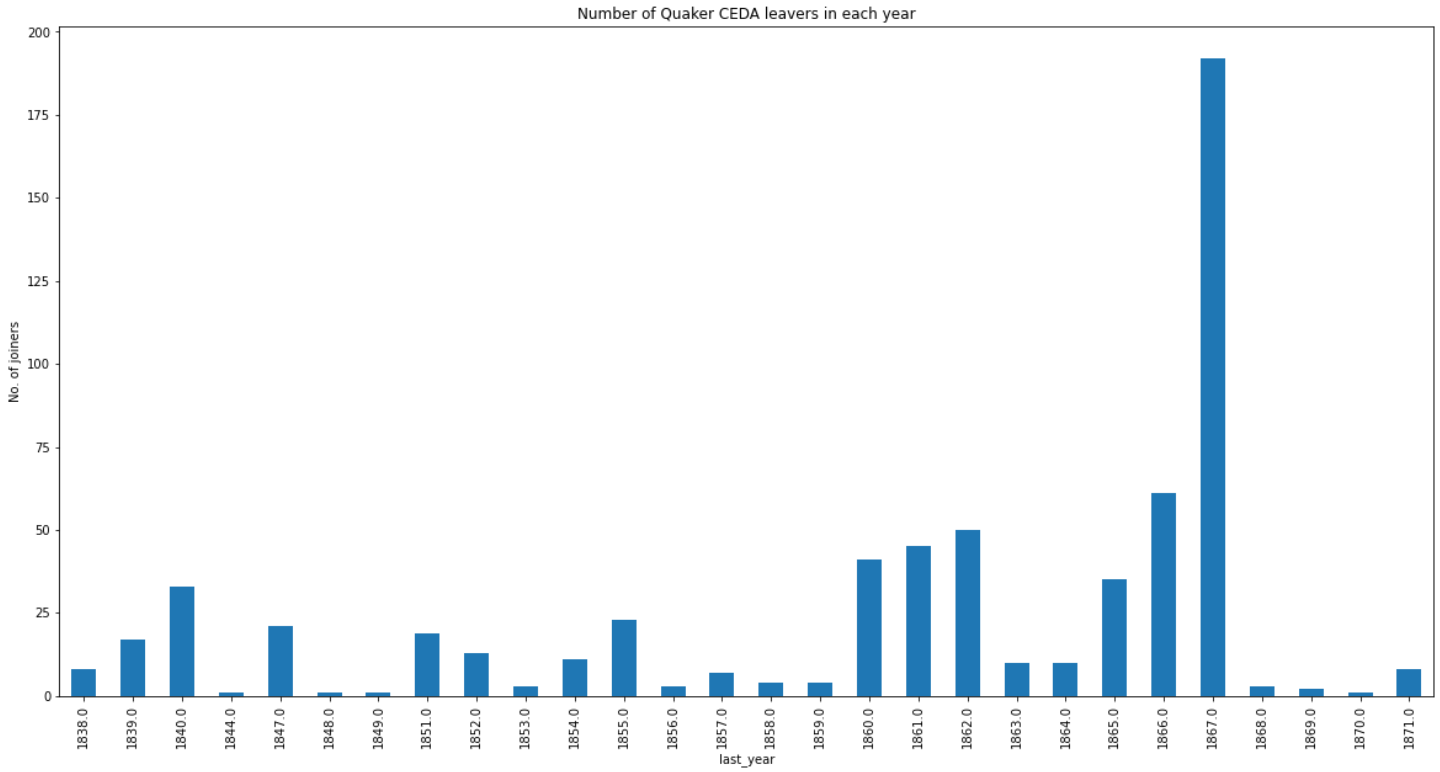
6.16 Quaker joiners of the CEDA by years

```
quaker_ceda.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker CEDA joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.17 Quaker leavers of the CEDA by years

```
quaker_ceda.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("Number of Quaker CEDA leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.18 Quaker members of the QCA

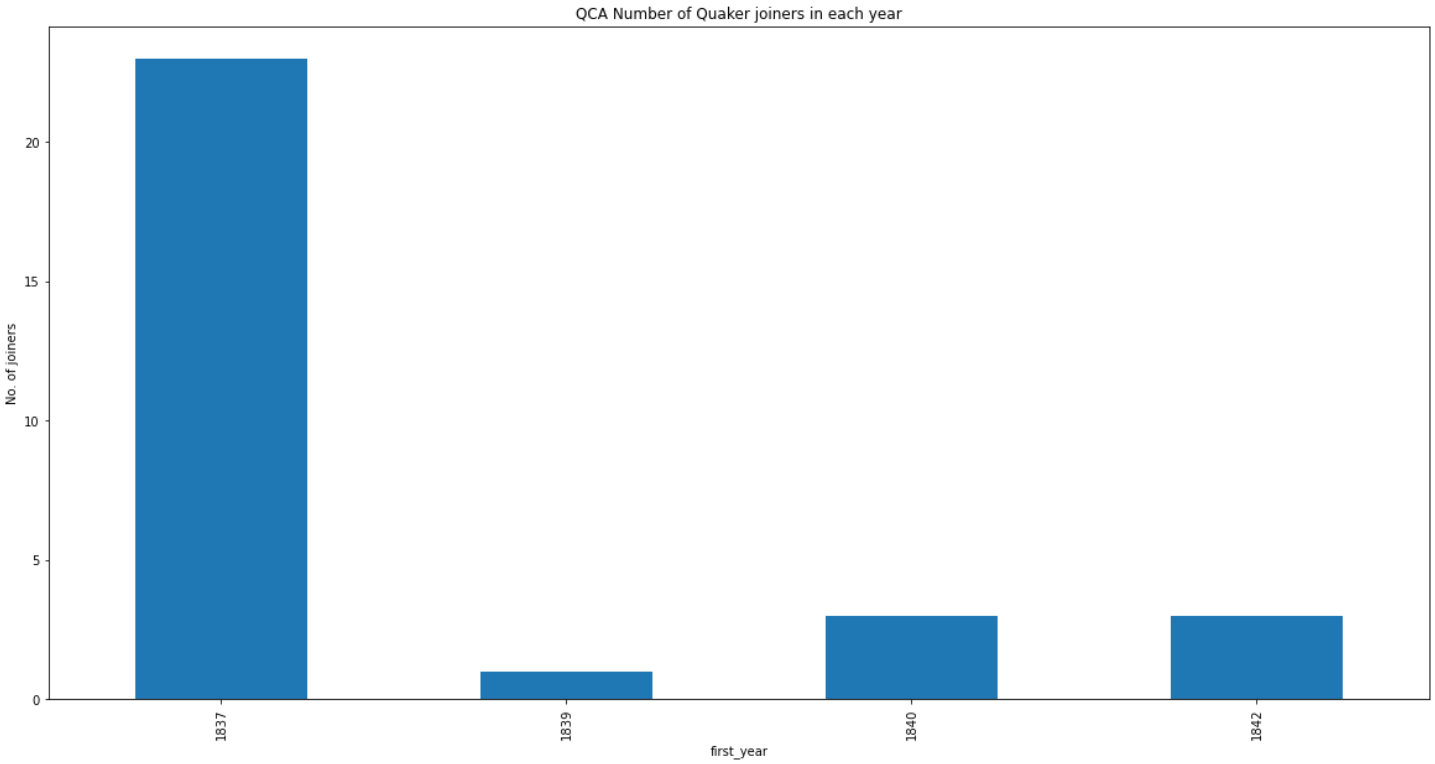
```
quaker_qca
```

	Name	religion_name	ceda_name	first_year	last_year
0	Thomas (1) Hodgkin	Quaker	QCA	1839	1847
1	James Bowden	Quaker	QCA	1842	1847
2	William Nash	Quaker	QCA	1842	1847
3	Joseph Sturge	Quaker	QCA	1842	1847
4	William Jun Grimshaw	Quaker	QCA	1840	1847
5	Henry Knight	Quaker	QCA	1840	1847
6	Edward Paull	Quaker	QCA	1840	1847
7	Robert Jun Alsop	Quaker	QCA	1837	1847
8	Abram Rawlinson Barclay	Quaker	QCA	1837	1839
9	John Barclay	Quaker	QCA	1837	1839

	Name	religion_name	ceda_name	first_year	last_year
10	Richard Barrett	Quaker	QCA	1837	1839
11	John Thomas Barry	Quaker	QCA	1837	1847
12	Peter Bedford	Quaker	QCA	1837	1847
13	John Bell	Quaker	QCA	1837	1839
14	Thomas Christy	Quaker	QCA	1837	1839
15	Samuel Darton	Quaker	QCA	1837	1839
16	Josiah Forster	Quaker	QCA	1837	1847
17	Robert Forster	Quaker	QCA	1837	1847
18	William Forster	Quaker	QCA	1837	1847
19	Joseph Talwin Foster	Quaker	QCA	1837	1847
20	John Hamilton	Quaker	QCA	1837	1839
21	Edwd Harris	Quaker	QCA	1837	1847
22	Geo Holmes	Quaker	QCA	1837	1839
23	Robert Howard	Quaker	QCA	1837	1839
24	John Kitching	Quaker	QCA	1837	1839
25	Joseph Neatby	Quaker	QCA	1837	1847
26	John Sanderson	Quaker	QCA	1837	1847
27	Joseph Shewell	Quaker	QCA	1837	1839
28	George Stacey	Quaker	QCA	1837	1847
29	Joseph Storrs	Quaker	QCA	1837	1847

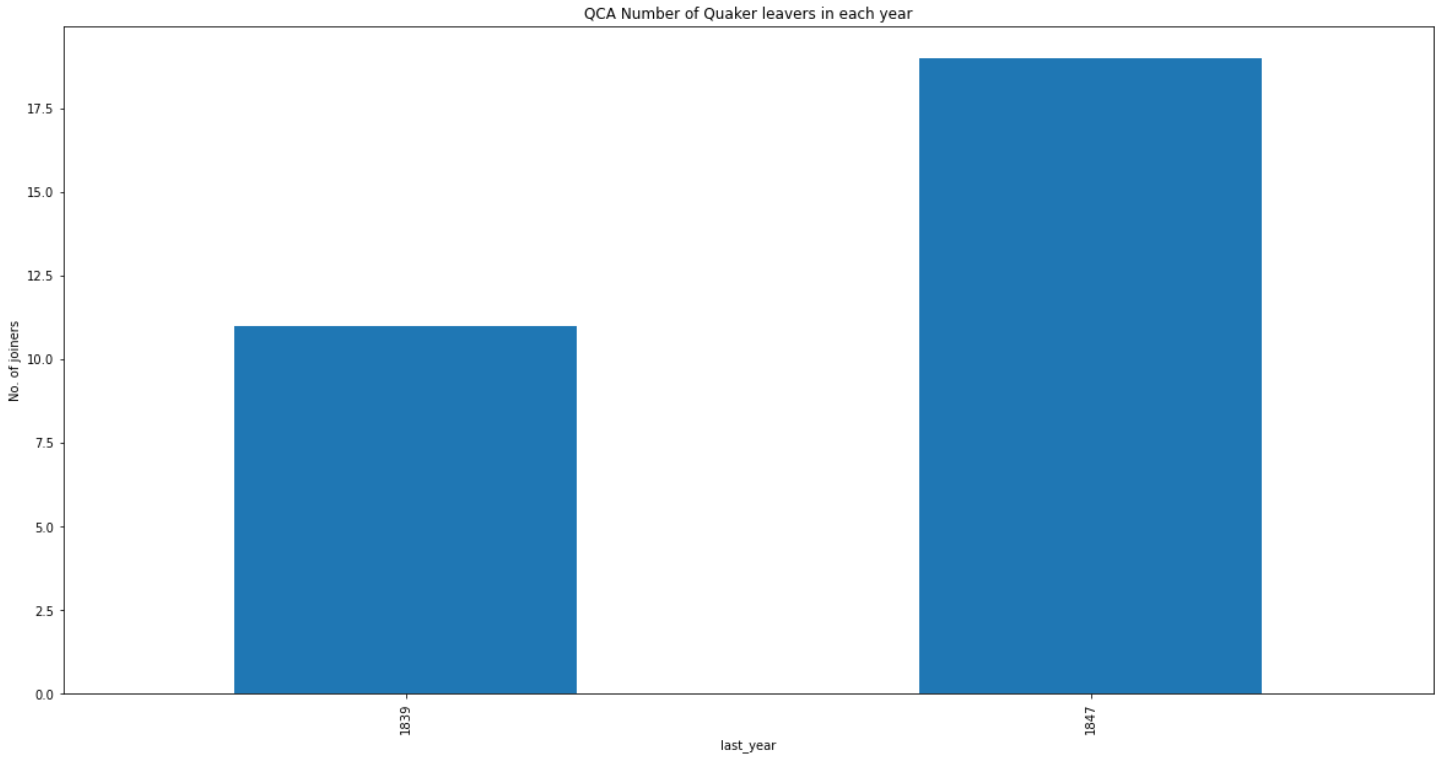
6.19 Quaker joiners of the QCA in years

```
quaker_qca.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("QCA Number of Quaker joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.20 Quaker leavers of the QCA in years

```
quaker_qca.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("QCA Number of Quaker leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.21 Show the Quaker members of the APS

Note Quakers make up roughly half of the members over all years

6.22 Quaker members of the APS - distant relationships

6.23 Quaker members of the APS - close relationships

6.24 Quaker members of the APS - immediate relationships

6.25 Show quaker members of the APS

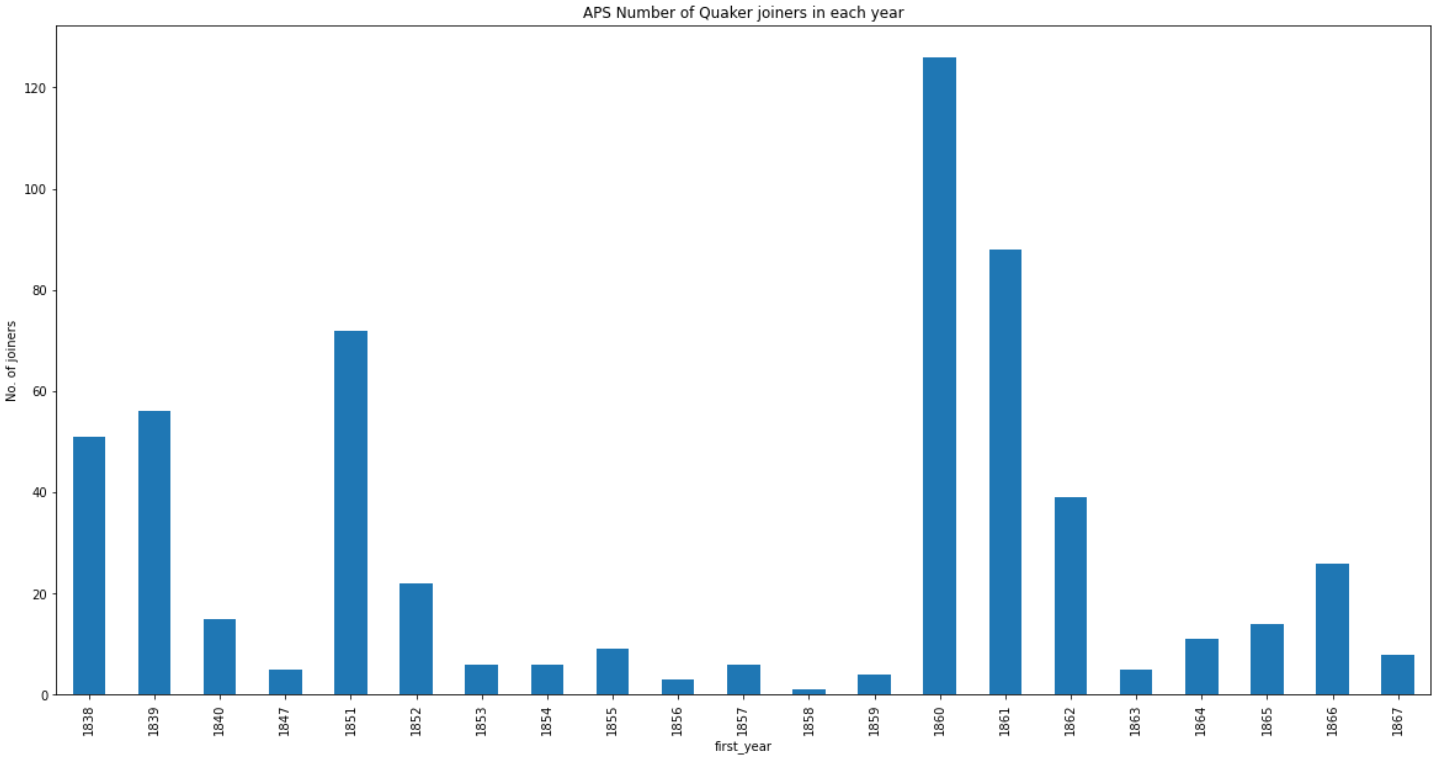
```
quaker_aps
```

	Name	religion_name	ceda_name	first_year	last_year
0	William Spicer Wood	Quaker	APS	1864	1867
1	William Wilson	Quaker	APS	1838	1865
2	James Wilson	Quaker	APS	1862	1867
3	E T Wakefield	Quaker	APS	1853	1864
4	John Ross	Quaker	APS	1839	1852
...	...	...	...	...	...
568	Joshua Wilson	Quaker	APS	1860	1860
569	F Woodhead	Quaker	APS	1861	1862
570	W Woolston	Quaker	APS	1861	1861
571	Francis Wright	Quaker	APS	1838	1838
572	S W Wright	Quaker	APS	1861	1861

573 rows × 5 columns

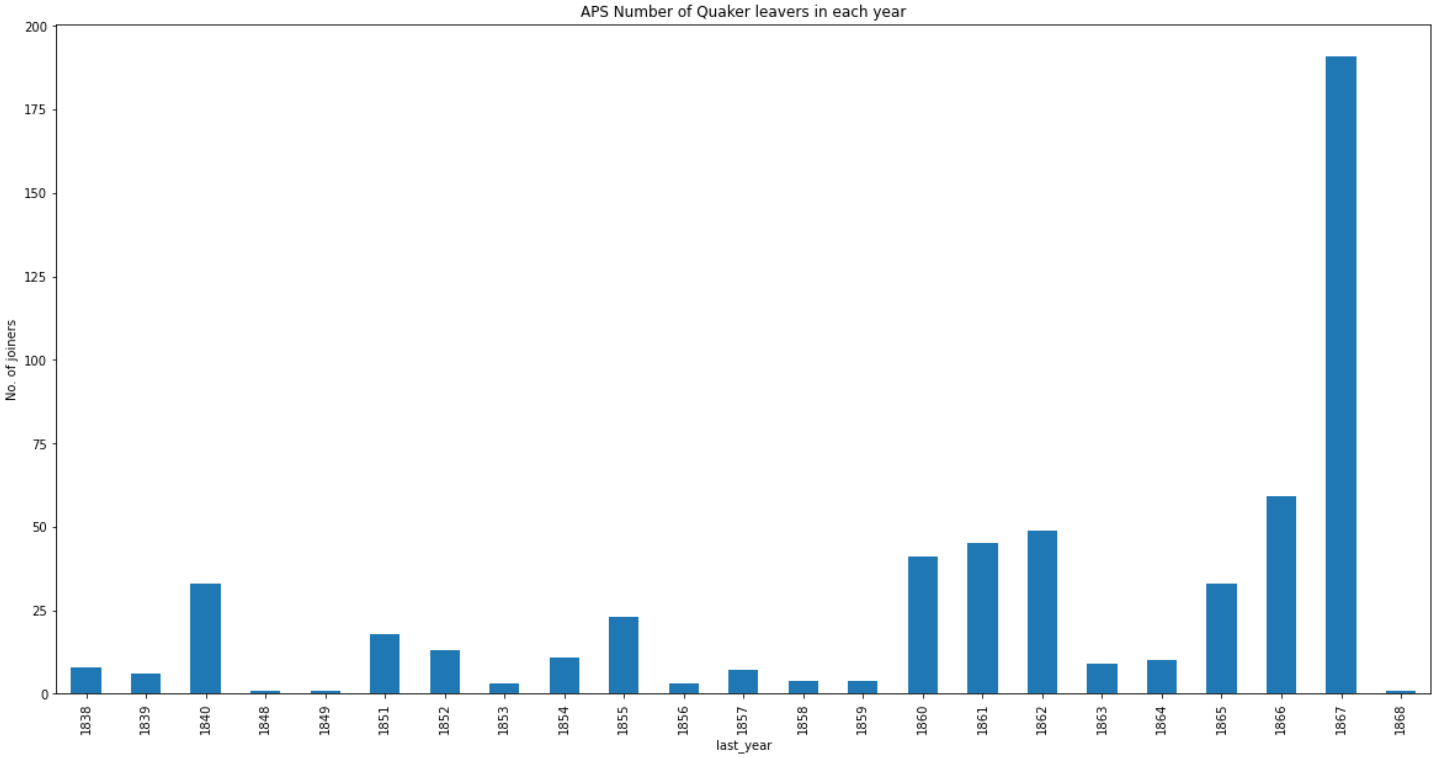
6.26 Pie chart Quaker joiners of the APS

```
quaker_aps.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("APS Number of Quaker joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.27 Pie chart Quaker joiners of the APS

```
quaker_aps.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("APS Number of Quaker leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.28 Show Quaker members of the ESL

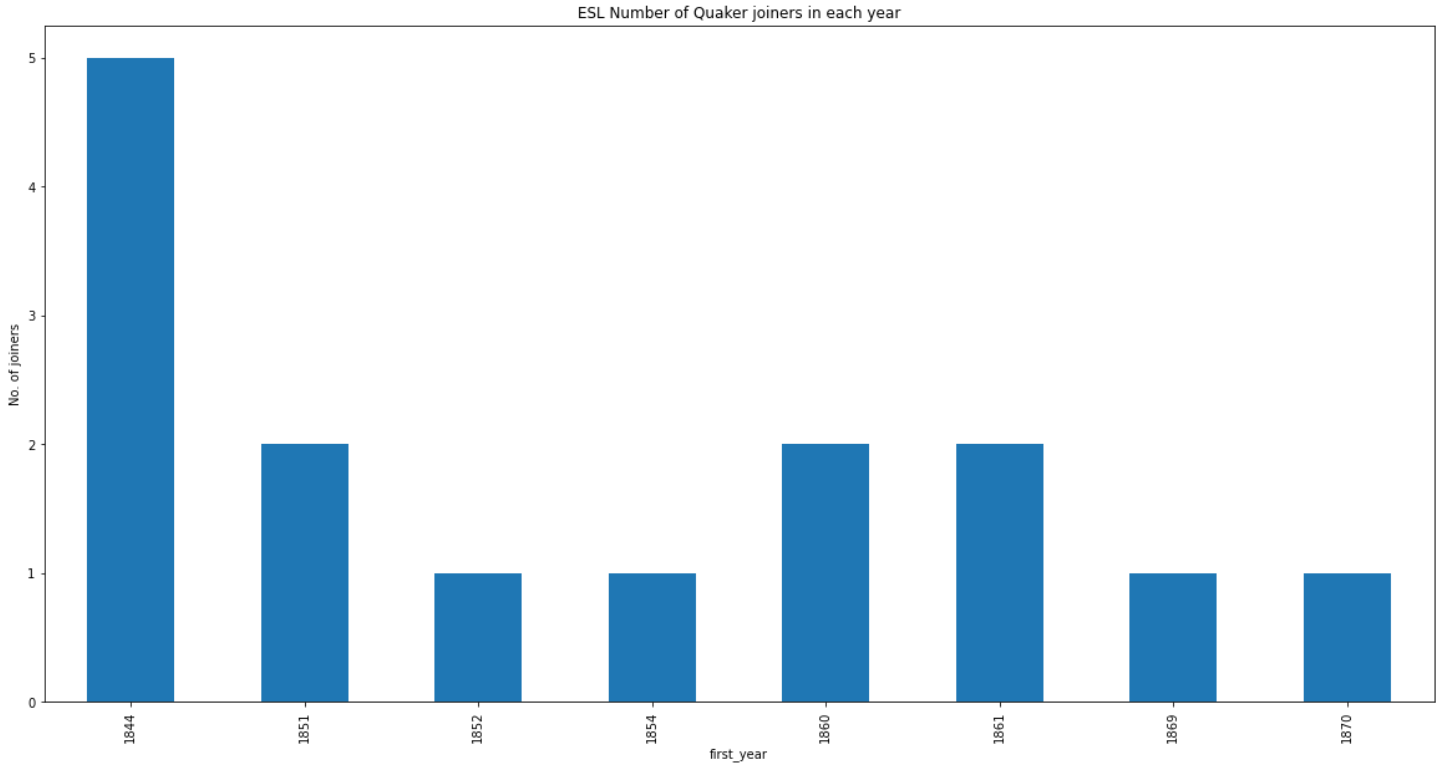
```
quaker_esl
```

	Name	religion_name	ceda_name	first_year	last_year
0	William Horton Lloyd	Quaker	ESL	1844	1847
1	Joseph Lister	Quaker	ESL	1844	1847
2	Thomas (1) Hodgkin	Quaker	ESL	1844	1862
3	John Henry Gurney	Quaker	ESL	1860	1867
4	Charles Henry Fox	Quaker	ESL	1861	1871
5	William Fowler	Quaker	ESL	1851	1851
6	Robert Nicholas Fowler	Quaker	ESL	1851	1871
7	David Dale	Quaker	ESL	1860	1863
8	x Collier	Quaker	ESL	1844	1844
9	William Clay	Quaker	ESL	1861	1868

	Name	religion_name	ceda_name	first_year	last_year
10	Henry Christy	Quaker	ESL	1854	1865
11	James Bell	Quaker	ESL	1852	1862
12	James (1) Backhouse	Quaker	ESL	1869	1869
13	Edward Backhouse	Quaker	ESL	1870	1871
14	William Aldam	Quaker	ESL	1844	1848

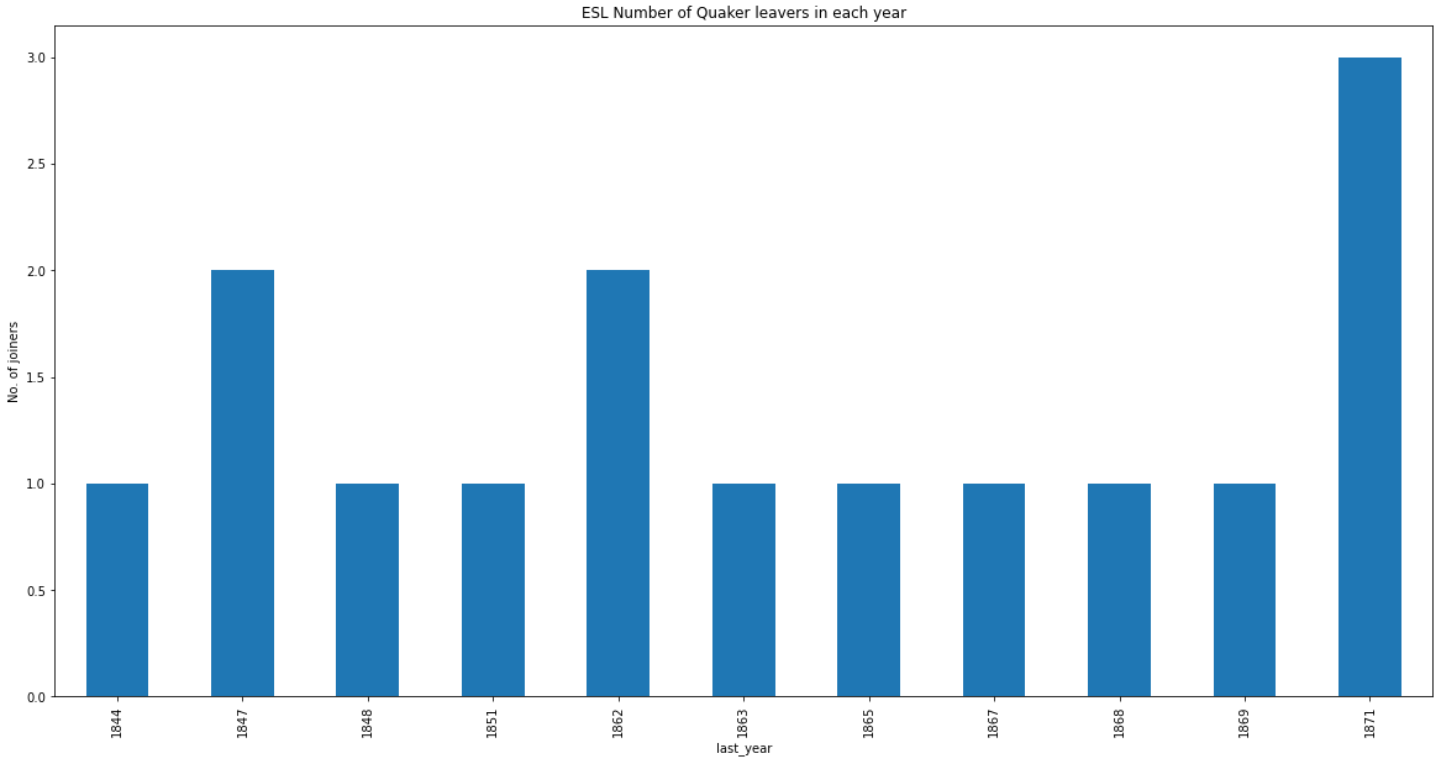
6.29 Show Quaker joiners of the ESL

```
quaker_esl.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("ESL Number of Quaker joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.30 Show Quaker joiners of the ESL

```
quaker_esl.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("ESL Number of Quaker leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



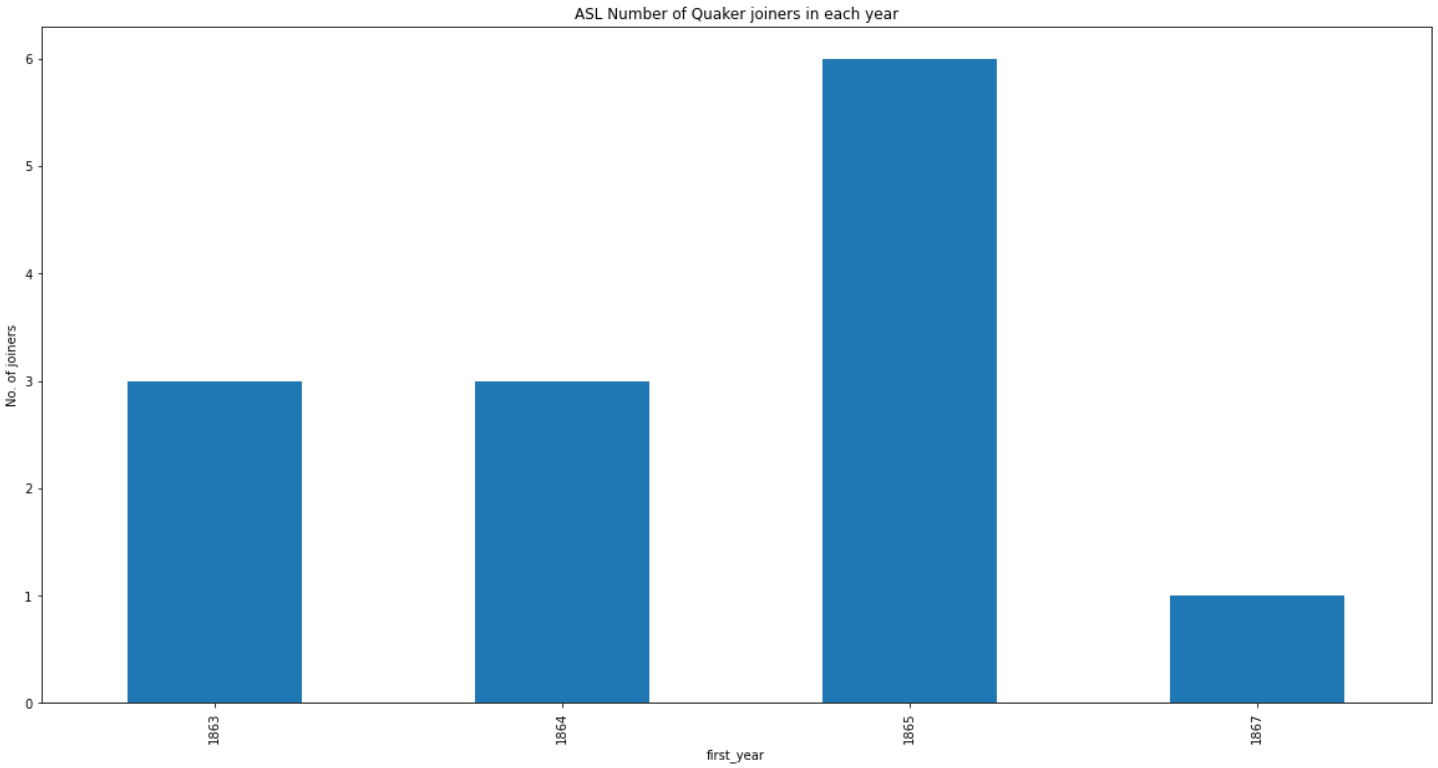
6.31 Show Quaker members of the ASL

```
quaker_asl
```

	Name	religion_name	ceda_name	first_year	last_year
0	William Spicer Wood	Quaker	ASL	1863	1871
1	William Wilson	Quaker	ASL	1865	1866
2	James Wilson	Quaker	ASL	1865	1865
3	E T Wakefield	Quaker	ASL	1865	1868
4	J Robinson	Quaker	ASL	1865	1865
5	Jonathan Hutchinson	Quaker	ASL	1863	1871
6	William Holmes	Quaker	ASL	1865	1869
7	George Stacey Gibson	Quaker	ASL	1864	1866
8	James T J Doyle	Quaker	ASL	1865	1868
9	Henry Crowley	Quaker	ASL	1864	1871
10	William Bull	Quaker	ASL	1867	1871
11	Antonio Brady	Quaker	ASL	1864	1871
12	S Stafford Allen	Quaker	ASL	1863	1870

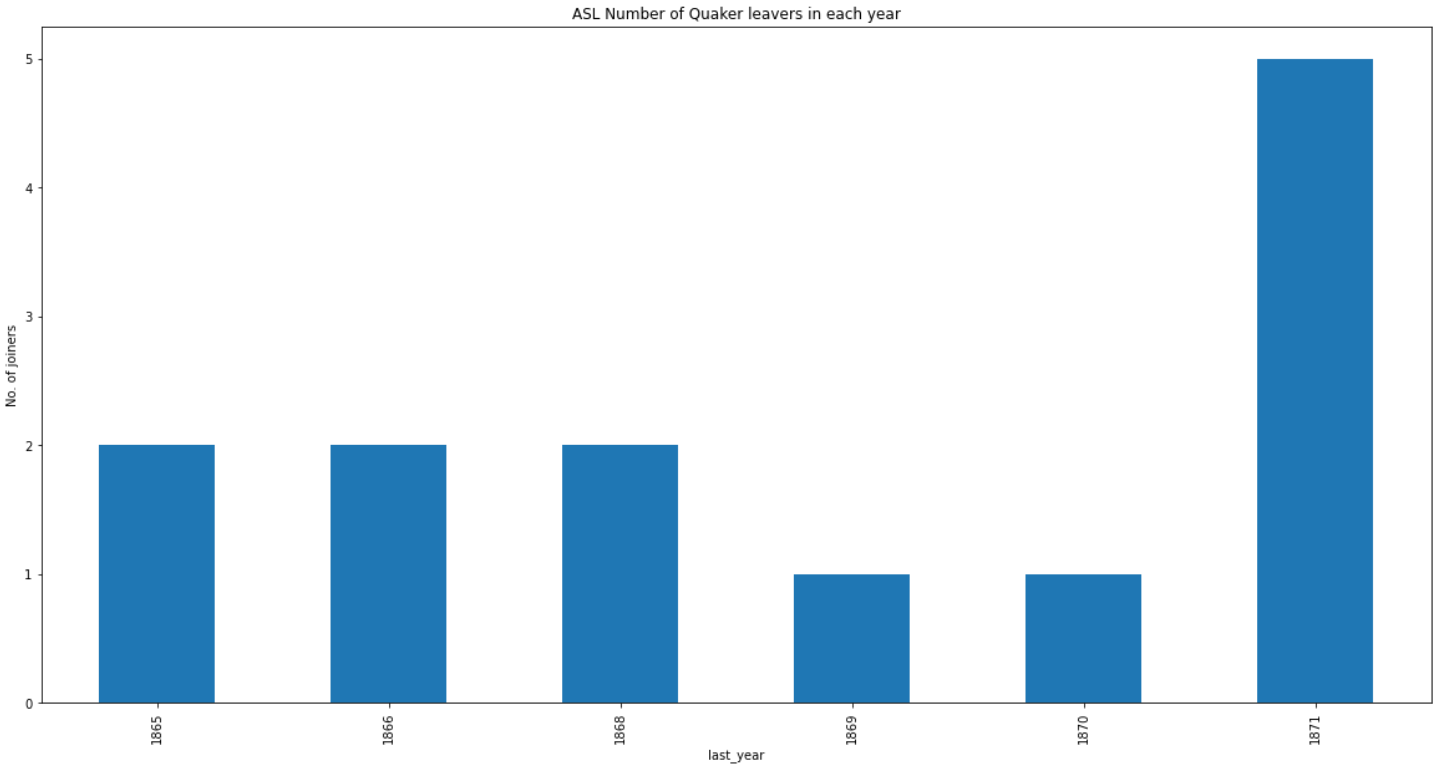
6.32 Show quaker joiners of the ASL

```
quaker_asl.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("ASL Number of Quaker joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.33 Show quaker joiners of the ASL

```
quaker_asl.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("ASL Number of Quaker leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



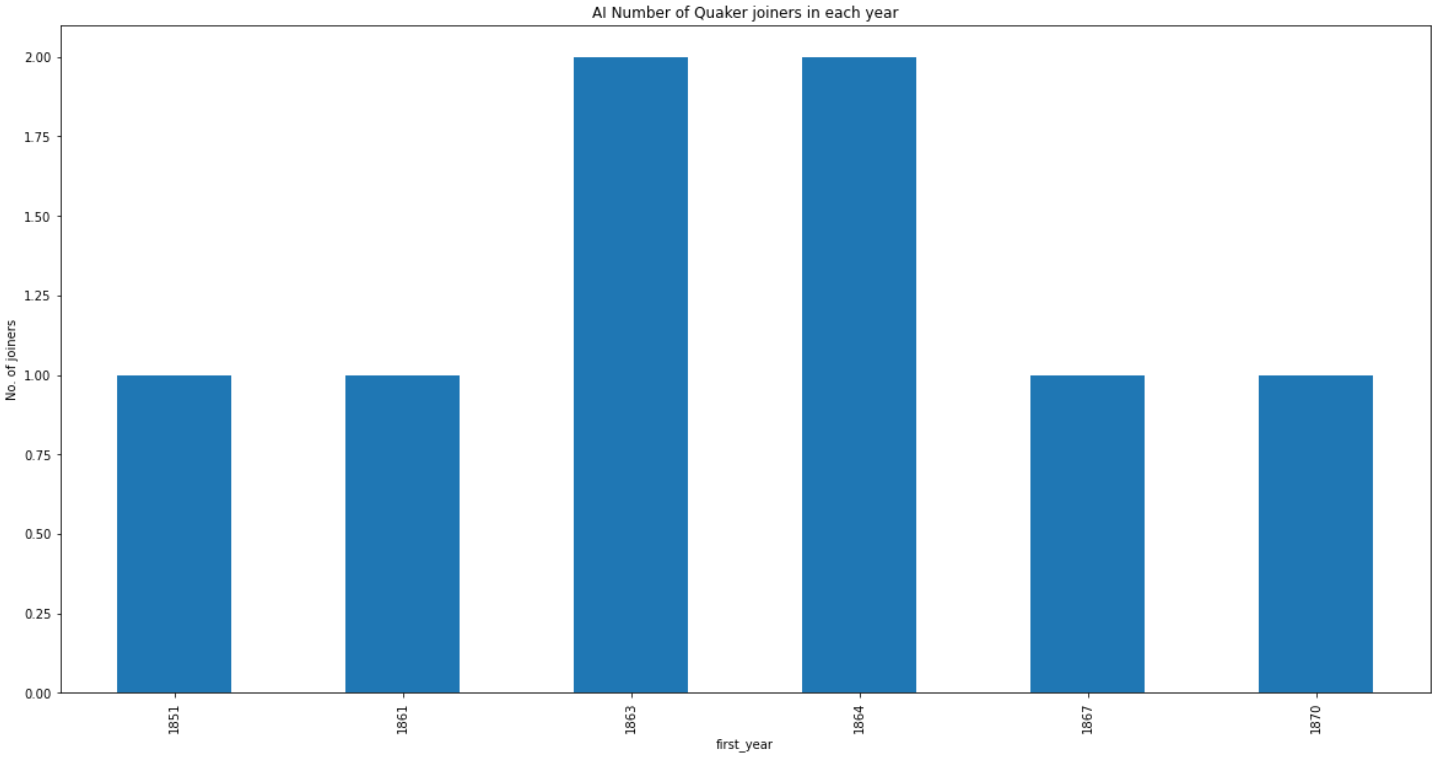
6.34 Show Quaker members of the AI

```
quaker_ai
```

	Name	religion_name	ceda_name	first_year	last_year
0	William Spicer Wood	Quaker	AI	1863	1871
1	Jonathan Hutchinson	Quaker	AI	1863	1871
2	Charles Henry Fox	Quaker	AI	1861	1871
3	Robert Nicholas Fowler	Quaker	AI	1851	1871
4	Henry Crowley	Quaker	AI	1864	1871
5	William Bull	Quaker	AI	1867	1871
6	Antonio Brady	Quaker	AI	1864	1871
7	Edward Backhouse	Quaker	AI	1870	1871

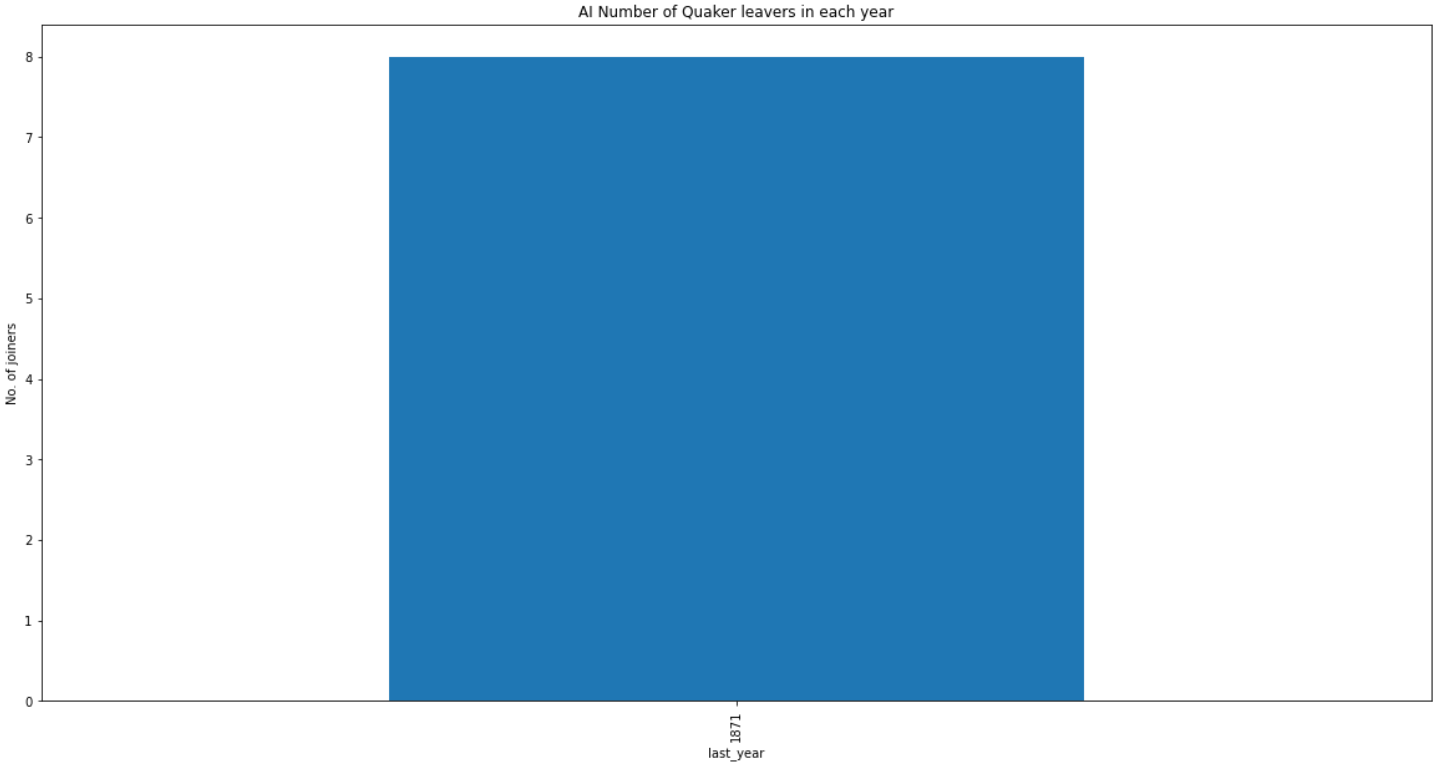
6.35 Show Quaker joiners of the AI

```
quaker_ai.groupby('first_year')['Name'].nunique().plot(kind='bar')
plt.title ("AI Number of Quaker joiners in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.36 Show Quaker joiners of the AI

```
quaker_ai.groupby('last_year')['Name'].nunique().plot(kind='bar')
plt.title ("AI Number of Quaker leavers in each year")
plt.ylabel ("No. of joiners")
plt.show()
```



6.37 Quaker CEDA members of Case Study Three Hodgkin's network

Note There are no 'first' and 'last' year data for this dummy CEDA

```
quaker_hod
```

	Name	birth_year	death_year	religion_name	ceda_name
0	E T Wakefield	NaN	NaN	Quaker	HOD
1	John Ross	NaN	NaN	Quaker	HOD
2	J Robinson	NaN	NaN	Quaker	HOD
3	Joseph Lister	1827.0	1912.0	Quaker	HOD
4	Thomas (1) Hodgkin	1798.0	1866.0	Quaker	HOD
5	Thomas (1) Hodgkin	1798.0	1866.0	Quaker	HOD
6	Robert Nicholas Fowler	1828.0	1891.0	Quaker	HOD
7	Henry Christy	1810.0	1865.0	Quaker	HOD
8	James (1) Backhouse	1794.0	1869.0	Quaker	HOD
9	James (1) Backhouse	1794.0	1869.0	Quaker	HOD
10	Jonathan Backhouse	NaN	NaN	Quaker	HOD
11	W G Gibson	NaN	NaN	Quaker	HOD
12	x Hadfield	NaN	NaN	Quaker	HOD
13	Thomas Harvey	NaN	NaN	Quaker	HOD
14	Thomas Hughes	NaN	NaN	Quaker	HOD
15	S Rickman	NaN	NaN	Quaker	HOD
16	Richard Smith	NaN	NaN	Quaker	HOD
17	W Thompson	NaN	NaN	Quaker	HOD
18	Frederick Tuckett	NaN	NaN	Quaker	HOD
19	Frederick Tuckett	NaN	NaN	Quaker	HOD
20	Joseph Sturge	NaN	NaN	Quaker	HOD
21	Robert Jun Alsop	NaN	NaN	Quaker	HOD
22	Peter Bedford	NaN	NaN	Quaker	HOD
23	Josiah Forster	NaN	NaN	Quaker	HOD
24	Josiah Forster	NaN	NaN	Quaker	HOD
25	William Forster	NaN	NaN	Quaker	HOD
26	Robert Howard	NaN	NaN	Quaker	HOD

	Name	birth_year	death_year	religion_name	ceda_name
27	Robert Howard	NaN	NaN	Quaker	HOD
28	R D Alexander	NaN	NaN	Quaker	HOD
29	J Gurney Barclay	NaN	NaN	Quaker	HOD
30	Joseph B Braithwaite	NaN	NaN	Quaker	HOD
31	Edward Carroll	NaN	NaN	Quaker	HOD
32	Elliott Cresson	NaN	NaN	Quaker	HOD
33	Elliott Cresson	NaN	NaN	Quaker	HOD
34	James Cropper	NaN	NaN	Quaker	HOD
35	Burwood Godlee	NaN	NaN	Quaker	HOD
36	Anna Gurney	NaN	NaN	Quaker	HOD
37	Anna Gurney	NaN	NaN	Quaker	HOD
38	Samuel Gurney	NaN	NaN	Quaker	HOD
39	Samuel Gurney	NaN	NaN	Quaker	HOD
40	John Barton Hack	NaN	NaN	Quaker	HOD
41	John Hodgkin	NaN	NaN	Quaker	HOD
42	John Hodgkin	NaN	NaN	Quaker	HOD
43	Luke Howard	NaN	NaN	Quaker	HOD
44	Luke Howard	NaN	NaN	Quaker	HOD
45	William Howitt	NaN	NaN	Quaker	HOD
46	Andrew Johnston	NaN	NaN	Quaker	HOD
47	Joseph Pease	NaN	NaN	Quaker	HOD
48	Joseph Whitwell Pease	NaN	NaN	Quaker	HOD

6.38 Quaker CEDA members not in Case Study

Three

```
quaker_not_hod
```

	Name	religion_name	ceda_name	first_year	last_year
0	William Spicer Wood	Quaker	APS	1864	1867
1	William Spicer Wood	Quaker	ASL	1863	1871
2	William Spicer Wood	Quaker	AI	1863	1871
3	William Wilson	Quaker	APS	1838	1865
4	William Wilson	Quaker	ASL	1865	1866
...	...	...	...	...	...
634	Joshua Wilson	Quaker	APS	1860	1860
635	F Woodhead	Quaker	APS	1861	1862
636	W Woolston	Quaker	APS	1861	1861
637	Francis Wright	Quaker	APS	1838	1838
638	S W Wright	Quaker	APS	1861	1861

639 rows × 5 columns

P7 Chapter 7 Project Seven presentation

Thesis Chapter 6.24

File name: jnb_hddt_qsra_september_2021

7.1 An Evidence Based Prosopographical study of 3000 activists 1830-1870 and the 600

Quakers amongst them

Subject:

My own research has revealed the extensive social connectivity between the roughly 600 members of a ‘Quaker Led Network (QLN)’ and their involvement within a community of roughly 3000 persons, spread across four organisations in Britain active between 1830 and 1870, which the QLN network helped to set up and staff. I call these, the ‘Centres for the Emergence of Discipline of Anthropology in Britain’ (CEDA).

Question 1:

What can be revealed if a historian uses data science to study a large historical community over a long period of time by bringing together and integrating metadata from catalogues, indexes, and genealogical data?

Methodology:

I have designed, built and I am now using a suite of open-source and reproducible relational database technologies and digital analytic tools to visualise and scrutinise the entire community of some 3000 activists over 40 years (1830-1870), picking out the Quakers amongst them so that the community can be explored at both group and individual level. I am able to model the ‘connected’ relationships between the individual members of the CEDA through time, including kinship, education, occupations, locations and organisations.

Question 2:

What is the extent of Quaker involvement in the CEDA, over the 40 year time span researched, and was Quaker kinship as socially cohesive as (say) education or occupation amongst the wider community?

7.2 This is a code cell

```
# First we call up the python packages we need to perform the analysis:

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.rc('figure', figsize=(20, 10))
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('png', 'pdf')
from operator import itemgetter
import networkx as nx
from networkx.algorithms import community #This part of networkx, for community det
import nbconvert
import csv

# <img src="xxxx.png">
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[1], line 5
      3 import pandas as pd
      4 import numpy as np
----> 5 import matplotlib.pyplot as plt
      6 plt.rc('figure', figsize=(20, 10))
      7 from IPython.display import set_matplotlib_formats

ModuleNotFoundError: No module named 'matplotlib'
```

7.3 These are the resources in my container for this exercise

Resource containers are also GitHub repo's facilitating granular version control of all changes made to any resources

7.4 This is the structure of the SQLite database (ERD)

7.5 Relationships (other then CEDA) present in the data

This graph shows all of the popular bigraph data in the database. Including all data would result in a ‘hairball’ where data would be too dense to be capable of analysis at this (the highest) level. (See Most popular entities section below)

7.6 All persons are members of at least one CEDA

Society	abv.	Dates
Quaker Committee on the Aborigines*	QCA	1832/37 - 1846
Aborigines Protection Society	APS	1837 - 1919
Ethnological Society of London	ESL	1843 - 1871
Anthropological Society of London	ASL	1863 - 1871
Anthropological Institute	AI	1843 - 1871
London Anthropological Society**	LAS	1873 - 1874

- Origin Society included in this project but not recognised by RAI. ** not included in this project (beyond 1871 cut off date).

7.7 Quakers and their relationships

7.8 Working with a variety of datatables

A ‘complete’ dataset

Would be one like this, where all of the data can be contained witin a perfect rectangular block of cells (‘containers’) and every container contains only one data item and every data item can be located by the coordinates ‘Row n, Column n’

An ‘incomplete’ dataset

When historical data is used often some data is missing (permanently lost) and the HDDT is able to accept ‘Incomplete’ datasets. The HDDT does not lose functionality because of the incomplete nature of much historical data.

An ‘irregular’ dataset

The HDDT has been designed to accept Irregular datasets. The surviving evidence of the past is not only often Incomplete, it is frequently Irregular, where multiple datasets have different dimensions. (Either because the data in itself is intrinsically different or because different data collectors use different cataloguing methods)

For the HDDT a qualifying dataset is a data set of any dimensions, complete, incomplete or irregular. The only requirement is that all datasets must contain a single common containing one

universally shared data item. The HDDT requires all data sets to contain datatables that can be referenced to a PERSON (Name) in one of its rows.

Conflicts between dataset Person (Name)'s are resolved by adopting in this project by nominating the 'RAI dataset' as the 'Authority Index'. With careful matching of Person (Name)'s found in other datasets, the RAI naming rule applies throughout.

7.9 Introduction to bigraph analysis

Bigraph data statistics

Table	Rows	Columns	Exc?
ceda	6	1	Yes
person_ceda	3894	4	Yes
club	68	1	*
person_club	323	2	*
location	83	1	
person_location	2061	2	
occupation	93	1	
person_occupation	1883	2	
society	260	1	
person_society	1238	2	

- Due to low levels of poulation of 67 other clubs only the Athenaeum Club is included in analysis

7.10 Locations

Top 10 locations pie chart

Top 10 locations bigraph

We can see that London and ‘country’(sic) are the most populated locations. Because the ‘country’ location is an aggregate (and not a specific location) we can think of London and ‘country’ as a twin centre. Within the twin centre we can see the members of both London and ‘country’ locations and that the members of each are highly networked. We can also see that the London location contains many members who have no association with any other group (including ‘country’). London 1830 - 1870, was densely populated and so it is possible that members of the London location had other modes of association. Because the ‘country’ location is an aggregate we cannot make the same analysis to the same extent, it is possible that many members in (say) Newcastle had no association with other members in (say) Bristol. We can see the large group of members who were members of both London and ‘country’ locations. It is highly likely that these members served as conduits of communication and group cohesion. It is interesting to note that only 3 members of this London and ‘country’ group were members of groups outside of the twin centre.

Eight other location each have a membership of around 30 members (we can call these the satellites), all of the satellite groups relate directly to the twin centre with very few members associated with more that one satellite location.

Australia and Ireland have associations with both London and ‘country’. The German location is most closely associated with the ‘country’ group. All of the other locations are strongly associated with the London location.

Germany (far right) is the location least associated with London. Alex Nidda Genthe is the only member from Germany who is also a member of the London location. Friedrich Max Muller, Frederick Augustus Haverick and Gustav Oppert each network with ‘country’ members. William

Wilson Hunter is the only ‘country’ member who also appears in the Germany location. He and Gustav oppert also have a location connection with India.

7.11 Occupations

Top 10 occupations pie chart

Top 10 occupations bigraph

We can see that ‘medical’,’academic’ and ‘armed services’ together account for half of the members by occupation. We can also see that the largest three occupational categories each contain many members who have no association with any other occupational group. We can see that the medical categories contain many members who are also members of the other two principal categories (‘academic’ and ‘armed services’). It is highly likely that these members served as conduits of communication and group cohesion amongst the three principal occupational cegories.

Seven other occupations each have a range of members with literary the lowest and business the highest. All of the satellite groups relate directly to the triple centre with many members also associated with more that one other satellite occupation.

It is surprising the the least networked occupation is ‘church’ and perhaps less so that ‘business’ and ‘legal’are highly networked.

Several individuals form a web of interconnectedness between the members occupations.

7.12 Societies

Top 10 societies pie chart

Top 10 societies bigraph

We can see that ‘Geological Society’ and the ‘Royal Goegraphical Society’ together account for a significant number of members by society. The ‘Royal College of Surgeons’, the ‘Medical and Chirurgical Society’ and the ‘College of Physicians’ form the next largest cluster of memberships of societies. These two clusters each contain many members who have no association with any other society. We can see that the medical group and the geographical group have few members in common. The ‘Royal Society’ and the ‘Linnean Society’ in the centre have between them the greatest level of networking amongst all of the societies. It is highly likely that these members served as conduits of communication and group cohesion amongst the two principal society groups.

Many other societies have a range of members all of whom are highly interconnected. All of the satellite groups relate most closely to the ‘Royal Society’ and the ‘Linnean Society’ rather than to the two larger clusters. Many members of the smaller satellite societies are also associated with more that one other satellite occupation.

It is surprising the the least networked occupation is the ‘Royal College of Surgeons’ and perhaps less so that the ‘Geological Society’ and the ‘Royal Geographical Society’ are highly networked.

Several individuals form a web of interconnectedness between the members of societies.

7.13 Cubs

Clubs will not be analysed in this project but the Athenaeum club can be used as an attribute (because it is a singularity).

7.14 Most popular bipartite networks combined

1850 members of the community are recorded as members of 35 popular entities (Locations, occupations, societies and the Athenaeum Club). These entities make a sphere of popular interest graph where meetings between members concerning the CEDA may have taken place, equally they may also be places where members might meet up only infrequently or informally. The visual analysis of connectivity between members in single societies and between members of multiple societies indicates the extent that the community is societally connected. The 1850 make up 60% of the entire community.

The graph at the head of this notebook shows the 1850 distributed by popular entity membership with the connectivity between them reflected in those members who are associated with more than one entity.

7.15 Iterative Section 1 - (This is an iterative workbook)

As can be seen in the illustrative graph above which has been produced in Gephi by the code cells below to provide an initial overview of the data and its distribution, the graph might be made more meaningful if it did not include societies sparsely populated.

The code cell below and the code cells in the section Iterative Section 2 (below) have therefore been designed so that a second run through the workbook can be made where the second run uses data that excludes low populated occupations identified in the first run through.

```
# Second we call up the csv files generated from the SQL database that contain info
# locations and the community members associated with locations. As well as enablin
# we produce a 'node_names' file and a tuples file of edges_attributes to generate
# produce GefX files for Gephi.

# We can run the code cell twice, first with all data and once all data has been ex
# and a decision made to exclude 'noise' the code block can be run again with newly
# csv files that exclude low populated locations.

#bipartite_10 = pd.read_csv ('vw_bipartite_10_names2_202108041622.csv')
bipartite_pick = pd.read_csv('vw_bipartite_pick_names2_202108051321.csv')

# Use these csv files in the 'with open' statements below to generate bipartite_10.
#names = pd.read_csv ('vw_bipartite_10_names_1_2_202108041606.csv')# For nodes csv
#tuples = pd.read_csv ('vw_bipartite_10_202108041605.csv')# For edges.csv

# Use these csv files in the 'with open' statements below to generate locations_10.
bipartite_pick_names = pd.read_csv ('vw_bipartite_pick_names_1_2_202108051304.csv')
bipartite_pick_tuples = pd.read_csv ('vw_bipartite_pick_202108051303.csv') # For ed


with open('vw_bipartite_pick_names_1_2_202108051304.csv', 'r') as nodecsv: # Open t
    nodereader = csv.reader(nodecsv) # Read the csv
    nodes = [n for n in nodereader][1:]# Retrieve the data (using Python list compr
                                       # to remove the header row
    node_names = [n[0] for n in nodes] # Get a list of only the node names

with open('vw_bipartite_pick_202108051303.csv', 'r') as edgecsv: # Open the file
    edgereader = csv.reader(edgecsv) # Read the csv
    edge_list = list(edgereader) # Convert to list, so can iterate below in for loo

    # Create empty arrays to store edge data and edge attribute data
    edges = []
    edges_attributes = []

    # Fill the arrays with data from CSV
    for e in edge_list[1:]:
        edges.append(tuple(e[0:2])) # Get the first 2 columns (source, target) and
        # not used this time. edges_attributes.append(tuple(e[2:4]))
        # Get the 3rd and 4th columns (first_year, last_year) and add to array

edge_names = [e[0] for e in edges] # Get a list of only the edge names
```

7.16 listing out the data

```
# List out the societies to be analysed

# bipartite_10
```

```
# List out the community members who have been associated with at least one selecte

# names
```

```
# Finally list out the tuples of members and societies
# (Note - some members are associated with more that one society)

# tuples
```

7.17 Use pyplot to make an inital visualisation of the data

We can see that many occupations are thinly populated.

We can also see that whilst 'Royal college of Surgeons',Geological Society' and 'Royal Geographical Society' are the largest societal segments several other occupations are well represented.

none of the inital segmentation requires qualification.

```
tuples.groupby('Target')['Source'].nunique().plot(kind='pie')
plt.title ("Popular_bipartite id")
plt.xlabel ("Group")
plt.ylabel ("Number of persons")
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-6-b54b19db52e7> in <module>
----> 1 tuples.groupby('Target')['Source'].nunique().plot(kind='pie')
      2 plt.title ("Popular_bipartite id")
      3 plt.xlabel ("Group")
      4 plt.ylabel ("Number of persons")
      5 plt.show()

NameError: name 'tuples' is not defined
```

7.18 Iterative Section 2 - prepare the data for rendering as a graph in Gephi

Caution - this section depends on the selections made under ‘Iterative Section 1’ above

If the initial analysis suggests that a more insightful visualisation might be made by refing the data to be analysed, return to the database and make a new Nodes (Names) csv file and a new Tuples csv file conaining only well populated groups.

Then return to Iterative Section 1 codeblock in the workbook and replace the csv files in the ‘with open’ code lines with the refined datasets.

Finally reset the nx.write_gexf (xxx.gexf) xxx statement to a new file name.

Then run all code blocks again and make a more insightful gexf file. Use that to produce an improved network graph for Stage 2 analysis.

Warning. - Ensure that the statement ‘nx.write_gexf’ in the last code cell in this section points to a new output file for Gephi. (eg., G, ‘xxxx_10.gexf’)Failure to set this value correctly will result in the previously generated .gexf file being overwritten instead.

```
print("Nodes length: ", len(node_names))
print("Edges length: ", len(edges))
# not used this time. print("Edges attributes length: ", len(edges_attributes)) # T
```

```
# First check that the data is correctly formatted

print("First 5 nodes:", node_names[0:5])
print("First 5 edges:", edges[0:5])
# not used this time. print("First 5 edges attributes:", edges_attributes[0:5])

# The output will appear below this code cell.
```

```
# We use NetworkX to build the graph data into a table

G = nx.Graph()
G.add_nodes_from(node_names)
G.add_edges_from(edges)
print(nx.info(G))
```

```
# Finally we can write a gexf file which will be placed in the root directory.
# We can then open the file in Gephi and visualise the network.

#nx.write_gexf(G, 'bipartite_pick.gexf')
```

7.19 Stage 2 - Bipartite analysis with 'noise' removed

We now re-run the code to generate a new gexf file for gephi. We use the refined pair of nodes (Names) and Tuples files generated in the SQL database that include only the top 17 groups.

```
bipartite_pick
```

```
bipartite_pick_tuples
```

7.20 Simplified graphs can be analysed more easily

```
bipartite_pick_tuples.groupby('Target')['Source'].nunique().plot(kind='pie')
plt.title ("Bipartite_pick id")
plt.xlabel ("Groups")
plt.ylabel ("Number of persons")
plt.show()
```

The community members most well connected (60%) are densely networked indicating that the CEDA members are able to bring to the task of developing the discipline of anthropology in Britain

considerable shared skills, information and knowledge.