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Ghosts and the machine: testing the use of Artificial Intelligence to deliver historical life course biographies from big data

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ABSTRACT

This article presents the findings of an experiment in the use of Artificial Intelligence text generation processes to convert historical ‘big data’ into narrative text. Using an extensive collection of records pertaining to the Australian colonial settlement of Norfolk Island in the South Pacific (1788–1814), we investigate Generative Large Language Model technology for converting tabulated data from the site into short pieces of novel text, describing the lives of transported convicts and free individuals recorded in our databases. These personalized stories are assessed for fluency and factual correctness. Using this process, we uncover some instructive problems and caveats. We detect AI’s inherent tendency toward bias and uncritical perspectives, including potentially offensive stereotypes. We also discover an unwelcome tendency to summarize data. So, whilst the outputs are for the most part effective and functional, we find that the best results still require artful human intervention to fully capture the most human aspects of history and heritage research.



KEYWORDS

Artificial intelligence; big data; Australian colonial history; biographies

Rapid advances in the electronic availability of historical documents, notably *via* the digitizing programs of major heritage institutions and private providers like Ancestry.com, have resulted in an explosion of tabulated data, as researchers transform the archive into structured records. Tabulated data, of course, has long been a favored means of capturing and processing historical (especially demographic) information, because of its potential to reveal complex trends, associations and comparisons (Reid-Green 1989). Modern technologies have both accelerated and democratized the process, contributing to a vast ‘new information ecosystem’ that is fundamentally transforming the historian’s craft (Milligan 2022). Currently, the management and use of ‘big data’ has most successfully involved data linkage and statistical analysis, especially for demographic and life-course studies. Certainly it is yielding substantial new insights in our own field of Australian colonial and convict studies where we benefit greatly from a nineteenth century proclivity for compiling personal information, often recorded as tables and statistics (Shoemaker and Ward 2016).¹ Elsewhere, text mining, semantic analysis and data visualization have contributed to the new ways of

making sense of complex historical patterns and phenomena (Graham 2017).²

In our research there are certain challenges posed, both by the sheer quantity and density of the information available in our datasets, but also by our need to address questions and obtain insights that are less mathematical in nature, especially for our industry and community end-users who may not have the contextual background, or the tools and time, to properly read and interpret our big data collations. We need ways of mining and presenting our datasets to increase their accessibility and appeal to a wider audience of history and heritage practitioners and consumers. To that end, we present our experiments with computational approaches to turning tabular datasets into narrativized text, where we generate short-form encyclopedic sketches, analogous to Wikipedia entries, for anyone requiring quick and accessible biographical sketches based on our data. In particular, we test the use of Artificial Intelligence (AI) as a ‘biographer’ and its utility in transforming tables into narratives that appear reasonably fluent and factually correct. Can we use AI to retrieve and narrate a life story from a set of transcribed tables? Can we conjure ghosts with a machine?

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This article outlines the approach and presents the findings of our experiment, which we hope provides an exemplary method for the future treatment of similar and larger biographically-orientated research datasets such as the monumental Digital History Tasmania project (Bradley et al. 2010; Cowley et al. 2021). However, as we explain, our work clearly demonstrates the limitations of uncontextualized data, particularly as it pertains to ‘capta’ (data that has been captured for a specific purpose, not just simply observed) (Hunsinger 2020). We also showcase some inherent biases in the AI text generation processes, proposing solutions to overcome contextual gaps while recognizing the current biases that must be considered when using AI generation tools in historical research contexts.

As we write, the number of publications dealing with AI is exploding, and in the cultural heritage sector AI is being broadly lauded for its potential to provide new and exciting opportunities (Magdalena 2023). Nevertheless, the technology still has a way to go before it is viewed as a mainstream tool by researchers and writers, despite the high likelihood that it is already being used naïvely by avocational historians/users, and certainly by students seeking an easily generated narrative.³ This lack of formal acceptance might be attributable to deficiencies in education and training for historians in digital skills, particularly in Australia where, arguably (certainly, in our opinion) we lag behind our international colleagues in terms of interest, infrastructure and digital literacy training (Jones and Piper 2024). Other inhibitors include concerns with security and cost (Bedué and Fritzsche 2022). We undertake this current study knowing that AI provides many opportunities for historical research and cultural heritage studies, but at the same time we wrestle, like many of our colleagues and peers, with a range of practical and epistemological questions arising from AI’s disruptive intrusion into the humanities. As humanists we write with a keen eye for the potential flaws and ethics of using AI.

Historical context

For our pilot project we generated stories about life and labor in the colonial settlement of Norfolk Island in the South Pacific during the so-called ‘first settlement’ phase (1788–1814), acknowledging that the episode was reasonably well documented and is of great interest to our students and the public. The settlement of Norfolk Island commenced in March 1788 with an advance party of 22 men (mostly convicts) sent from the Australian mainland to occupy the tiny island, located some 1400 km to the east of

Port Jackson (Sydney). They were soon joined by hundreds more military, convicts and free settlers, the population rapidly peaking at around 1,150 persons between 1792 and 1794. The island’s rich volcanic soils supported several small villages and the cultivation of numerous properties which were granted to free and military settlers who employed convict laborers. Although agricultural production thrived, the small size of the island, its isolation and the marked social divisions between and within groups sometimes saw difficult social and administrative situations including a simmering military uprising over land and issues pertaining to privileges and relationships with convict women (Gill 1976). By the mid-1790s these factors and escalating expenses led to calls to abandon the island, although that was resisted for the better part of another decade. A slow withdrawal commenced in 1805, amid a flurry of claims for compensation (Phelps 2022). Many were removed to Van Diemen’s Land (Tasmania) by 1813 and the island was completely abandoned in February 1814.

While its fortunes might have ebbed and flowed, the Norfolk Island ‘First Settlement’ episode seems an ideal location for researchers wishing to understand our colonial ancestors. For our purposes, it is a circumscribed and small space with a well-defined history of European occupation, where all inhabitants and visitors fell under the gaze of colonial administrators. Certainly, the managers of Norfolk Island were prolific recorders of information. The settlement was the subject of a near continuous run of systematically recorded administrative data, a lot of it captured in the form of ledgers and lists which are an enticing target for research as they are, of course, readymade for conversion into digital spreadsheets (see Figure 1). Over 100 such documents have been identified to date, amongst an even greater volume of correspondence and diaries. Surprisingly then, only recently have these resources been transcribed into a useful or publicly accessible format. Norfolk Island need no longer remain one of the best documented mysteries in Australia’s colonial past.

A number of these documentary materials are well known. The best and most used sources for the demography of Norfolk Island are the so-called ‘Victualing Books’ detailing who was being fed from the government stores (see Figure 1).⁴ There are in addition a number of ‘general musters’ held in the State Archives and Records Authority of New South Wales, and numerous lists of settlers and convicts that were compiled for various purposes and sent in official despatches to the Colonial Office in London.⁵ These sources formed the basis for pioneering efforts by historians to reconstruct what has been called ‘The

Civil Department 8 11

No.	Time of Entry			From Whence	Names	Quality	D.D. D R	Time When			Walter	Days Victualled			
	Month	Day	Year					Month	Day	Year		1792	1793	1794	1795
1	Nov	2	1791	Eng Land	Philip Sutley King	Gov. Governor	D	Feb	22	1796	for Norfolk Island	365	365	365	365
2	Mar	6	1788	for Norfolk Island	Thos. Sumner	Asst. Surgeon						365	365	365	365
3	Dec	13	1780	"	Stephen Dunonard	Milit. Justice	D	Nov	9	1793	for Norfolk Island	365	68	"	"
4	Nov		1790	Port Jackson	Thos. Freeman	By Commisn	D	March	30	1793	for Norfolk Island	365	89	"	"
5	"	"	"	"	Wm J. Dudge	Superintendent	D	Nov	10	1791	for Norfolk Island	"	"	"	"
6	"	"	"	"	D. Amy Westworth	Asst. Surgeon	D	Feb	17	1796	for Norfolk Island	365	365	365	365
7	Nov	4	1791	"	Wm. Bolman	Asst. Surgeon	D	Aug	0	1795	for Norfolk Island	365	365	365	210
8	Nov	4	1791	England	Wm. Madel Chapman	Storekeeper						365	365	365	365
9	Nov	11	1791	"	Charles Guine	W. Surgeon	D	Apr	2	1792	for Norfolk Island	264	"	"	see entry page 2
10	April	23	1792	Port Jackson	Franc. Edge	Proc. Marshal						365	365	365	365
11	Dec	22	1792	"	John Jamieson	Superintendent	D	April	2	1796	for Norfolk Island	9	365	365	365
12	Dec	22	1792	"	Wm. Peale	Asst. Surgeon	D	June	9	1795	"	9	365	365	170
				"	Andros Mame	Superintendent	D	Mar	9	1793	for Norfolk Island	365	68	"	"

Figure 1. Extract from Norfolk Island victualing book, 1792–1796. Source: State Records Authority of New South Wales <<https://collection.sl.nsw.gov.au/record/9NaApbWY>> (13 December 2023).

Forgotten Generation’ of Norfolk Island pioneers.⁶ Our research, however, has trawled an even greater number of materials, including the Royal Navy Ships’ Musters, maintained by The National Archives (for England and Wales) which disclose the fluidity of the early Norfolk Island population and reveals new identities—marines, soldiers, prisoners, civil servants and families—not noticed in the standard sources.⁷

Through this greater range of sources, we have identified just over 3,600 individuals associated with the settlement, a 30% increase on previous estimates.⁸ Via manual transcribing and evaluation, we generated over 17,500 data points from the available Norfolk Island documents, with an average of around 5 data points per person. Such a dataset has great utility, and it certainly lends itself to the standard types of statistical interpretation.⁹ There are, however, well-recognized shortcomings with the long-favored approaches to Australian colonial and convict history data. As Shlomowitz (1990) observed, datasets are prone to elevate the quantitative over the qualitative, and that is problematic when we are dealing with the intensely human impacts of phenomena such as colonialism, exile and forced labor (Evans and Thorpe 1992). Further, our numbers and statistics are derived from what were, essentially,

expressions of state bureaucracy and power, designed to surveil subordinate populations. On balance, despite the seemingly robust and clinical nature of the Norfolk Island records, these concerns are urgent and valid in the case of our research.

We therefore see much value in supplementing the statistical with a microcosmic approach, drawing out individuals from the dataset and combining subject matter expertise with data points to craft some textured picture of past lives.¹⁰ This biographical approach, we hope, evokes a sense of the lived experience, rescuing our subjects from imprisoning spreadsheets and re-humanizing them as agents of our past. Certainly, doing so at scale, for potentially thousands of individuals, is an ambition worthy of automation. But can AI text generation tools satisfactorily reconstruct an individual life from a spreadsheet? Can the concatenation of data points result in a legible, intelligent and reliable account of a past human experience?

AI as a biographer: some risks and management strategies

Modern computing capabilities have made statistical analysis of historical data much easier, at least in some

ways. Certainly, in our field of Australian crime and convict studies, statistics have made an enormous impact. Techniques and technologies have progressed a long way since the pioneering work of Lloyd Robson who, in the 1960s, used a statistical sampling of biographical data from the ‘convict indentures’ to describe the body of convicts transported to eastern Australia in the early nineteenth century. Tellingly, he shaped his vast body of economic and biometric data into what was essentially a subjective pronouncement on the moral character of the typical convict (Robson 1994).¹¹ Even the statistical analysis of the *Convict Workers* project, which in the 1980s propelled the historiography of convict Australia in fresh directions by steering away from cultural concerns toward an economic focus, now seems somewhat elementary given the acceleration of computing technology (Nicholas 1988). Modern exponents in the field such as Hamish Maxwell-Stewart, Mark Finanne, Kris Inwood, Alana Piper, Richard Tuffin, Barry Godfrey, Rebecca Kippen and others, have explicitly employed technology to revise and refute earlier assumptions in the literature. They have further demonstrated how the ability to synthesize and analyze big data facilitates better understandings of the bureaucratic processes once employed to monitor and control working class lives and labor.¹²

This is not to say that the actual data collection stages of this undertaking are necessarily easier. While it is true that computational text reading processes such as *Transkribus* and data matching tools have made serious headway and can accelerate the data collection process,¹³ it is equally true, in our experience, that the most valuable tool in the data collection chain is a group of well trained and enthusiastic transcribers and validators. Human intelligence and intuition remain the surest means of working through the myriad of spelling variations, abbreviations, writing styles and tabulation quirks that are hallmarks of colonial recordkeeping. In our work, as in others, manual deciphering and stenography remain critical to the curation of datasets.

Similarly, there has, until now, been no substitute for human intellect and effort in the generation of biographies. Until recently, computational techniques have been unable to transform data into narrativized stories, and so biography has remained a labor-intensive field. Advances in Artificial Intelligence (AI), however, provide a new and radical opportunity to remedy this situation, by ingesting research outputs and turning them into customized biographies which provide context around individual lived experience. The specific flavor of AI that we have adopted for this purpose is the Generative Large Language Model (LLM).

A full discussion of LLMs is beyond our brief, but a precis is needed to situate those elements of the technology that might give rise to potential issues. First and foremost, LLMs are principally text regurgitators. Trained on very large corpora (often hundreds of billions of data points) LLMs make statistical decisions on what sequences of words are most likely to follow other sequences of words, based on the combinations and patterns they have seen in their training data. While the word combinations most likely recited by a model can be altered through various parameters, many of them user controllable, at their core LLMs, at some level, always draw back on the word combinations they have been previously exposed to.

This deep embedding of statistical inference into the models does have some potentially negative implications for the use of LLMs in historical research. The first of these issues is bias. If the source training corpora contains potentially harmful bias, such as racial, religious and gender stereotypes, then despite the best efforts of model developers to prune them out, the sheer size of these models means that detecting and rectifying all instances is unlikely and bias will leak into outputs (Navigli, Conia, and Ross 2023).¹⁴ For cultural heritage this means that outputs may contain discredited constructs and exclusionary stereotypes. These behaviors need to be monitored and accounted for in any proposed use of the technology. Similarly, there are potential issues with the social context of the data—in our case criminals who may have committed heinous acts of violence and theft, but who are inadvertently contextualized in an inappropriately benign manner, or even recast in a positive light, based on the predominate undercurrent present in the LLM training data.

Closely related to this is factual integrity. In the same way AI can leak bias, they are equally capable of distributing information not based on fact and truth. The training of LLMs does not rely on any measure of referential or factual integrity and models have a poor grasp on the theoretical soundness of generated arguments (Liang et al. 2023). This is particularly relevant as one typical source of training data for LLMs is the open internet, where the popularity of an opinion is more likely to see it reproduced and therefore infiltrate the training data, regardless of its veracity.¹⁵ Allied to the occurrence of populist misrepresentation is the concept of ‘model hallucination.’¹⁶ In a strict sense, hallucination is the human phenomenon of ‘confabulation’ (false memory), but it also refers to how an LLM model will simply fill gaps with fabricated, misinterpreted, or distorted information.

These tendencies have serious implications for the production of historical and biographical outputs that are required to be grounded in provable fact. Indeed, this challenges the very hope that AI can satisfy our scholarly needs and instincts. The term ‘artificial’, after all, is synonymous with ‘fake’ and ‘fictitious’ (Hargreaves 2023).

What is called for in these circumstances is a risk management strategy, whereby the user of AI is cognizant of these issues and takes reasonable steps to mitigate the dangers. The mechanisms available include input control, model modification and output moderation. Input control largely revolves around the instructions that are sent to the AI to follow—a process known as *prompt engineering*. The nuances of prompt engineering vary from model to model but generally they adhere to the same basic principles. These principles might be best encapsulated in the notion of mentoring a writer who is functionally literate but is making an initial attempt to write in a particular style—perhaps learning to write a scholarly essay for the first time. In this scenario it would be useful to be very specific about the expected outcome and the steps required to get there, including the provision of examples wherever possible. Prompt engineering follows this same principle, with the instructions requiring a clear context and details about format, style and length of output. As well as providing the specifications and output examples, it is also possible to automatically inject specific, relevant source material into the prompt and to instruct the model to use that information in generating the output. This approach is known as Retrieval Augmented Generation (RAG) and remains the most accessible approach for the general user who does not have the capability or resources to train a model on their specific data (Cai et al. 2022).

Because of its accessibility, RAG has become widespread and has spawned many ancillary toolsets that automate the insertion of supplemental data into a prompt, streamlining the process for the user.¹⁷ It is a derivative of that process we adopted in our experiment, as explained below. When looking to utilize RAG, several factors should be considered. Firstly, the total maximum length of an input prompt varies model to model, and therefore the scope for supplying context also varies. Most publicly accessible (commercial and open source) models can accept prompts that are hundreds of words long but it is not a simple matter of more is better. There are cost implications. Commercial models charge on the number of input and output tokens they receive and generate (a token roughly represents $\frac{3}{4}$ of an English word, but this is a guideline

rather than a rule), so large prompts are more expensive to process. For example, in our dataset, a prompt with a fully RAG augmented context contains at least three times more text than a prompt with source data points alone. The cost impacts are similar for those running a model on their own hardware, with much higher specification (therefore costlier) machines required to run models capable of processing large prompts in a timely manner (or at all). Depending on the use case though, this can still be cost effective, or even desirable as the cost involved is justified by the quality of the output and the relatively smaller cost compared to a custom model, as we discuss now.

A second strategy for risk mitigation is to build a customized LLM model that better understands your subject matter. While it is possible to train models from first principles it is more common to fine-tune a preexisting model with user specific data, so that the outputs better reflect the user’s requirements. In this way a user gets access to an already performant model and does not bear the costs of building the model from scratch. In this approach the original model is seen largely as a ‘black box’, with the goal being to steer that model through the presentation of training data to the desired outcome. This type of training is well suited to introducing new ‘styles’ or behaviors to the model and can be used to correct unwanted behaviors such as cultural bias.

Traditionally, training a model has been highly resource intensive in terms of data preparation and computing resources, however the advent of LLMs as a commercial service has resulted in some ingenuity in this space. Developers have taken to the challenge and produced toolsets to turn user text into the most common formats for LLM training using existing tools such as natural language processing or, in some instances, using the LLMs themselves (Yu et al. 2024). Such tools have the potential to reduce the effort and costs of generating training data. There are still caveats, however. Many of the LLMs can perform some level of useful training with as few as 1000 examples, although better results are normally achieved with more examples. Care must be taken however not to over train the model, reducing its ability to respond to new situations, thus a large commitment to understanding the mechanisms and impacts of training is still required (Zhang et al. 2024). There is also the quality control issue. Just because a software package can assist in generating training data, it does not follow that the data conveys the lessons you want the model to learn or the true meaning of your data. So, a human/manual review process is still highly recommended.

This brings us to the third risk management strategy: output moderation. There is no simple approach to this task. It is highly dependent on the outputs that an LLM is asked to generate and how quickly those outputs are delivered to the user. Take for example, a system developed to take a user-provided question and generate a corpus-specific answer to that question in real time (the chat model). In this scenario it is almost impossible to moderate the outputs with any degree of success. At the other end of the spectrum (and the method employed in our research) the LLM produces outputs which can be moderated before being presented to the consumer. This is still labor intensive, but with the current technology it has the greatest opportunity of producing the highest quality outputs.

Ultimately, each of these three strategies need to be considered when working with highly specific personal data (Richards and King 2014). The particular ethical implications will vary from use case to use case. In terms of our own work, we are satisfied that we are reasonably relieved of the ethical and legal questions confronting DNA research on human remains or family artifacts, for example (Kowal et al. 2023; McKibbin, Shabani, and Larmuseau 2023). We know with absolute certainty that the persons represented in our data are deceased, and that the resurrection of their stories today is for distinctly benign and fair purposes. And yet, we are also cognizant of a growing awareness of the moral dimensions of family and local history research—our data has many lineal links to living persons and genealogists and local historians are a major consumer of our research outputs (Moore 2023). And as noted earlier, we also recognize that we are transforming and indeed perfecting what were once state mechanisms for the surveillance and measurement of human behavior and output. We are helping build what Barry Godfrey has called a ‘Digital Panopticon’ (Godfrey 2022). Each researcher will be (as we are), driven by the ethics and research policies of their discipline and respective institution, but there are emerging communities of best practice (such as data for democracy) currently working on some specific ethical guidelines for dealing with big data approaches (Ruijter, Grimmelikhuijsen, and Meijer 2017).

Methodology

In our research, the model used is a combination of big data parsing and prompt engineering (including RAG). It does not involve any model training and could therefore be easily adapted to any similar use

cases by other history and heritage researchers. While open source and free for noncommercial purpose LLMs were considered (such as LLaMA and Bloom), we opted for the proprietary OpenAi *GPT4 Turbo* model.¹⁸ The choice to use a commercial model was largely based on expediency and hardware availability, allowing all the computationally intensive tasks to be offloaded to the commercial AI servers, while still running the data preparation and moderation tasks on standard ‘at home’ desktop class hardware. This mitigated purchasing and procurement risks while still being performant enough to draw reasonable conclusions on viability.

In preparation for the study, the 107 source documents transcribed by volunteers and research assistants into spreadsheet format were validated (or quality-checked). In this process transcription errors were corrected; missing data points were researched, and a standardized list of individuals were identified and assigned a unique ID number to ensure they could be distinguished and tracked across the full dataset. As noted above, this resulted in a directory of 3,500 uniquely identified individuals (Roberts and Cathy 2024).

The next step was to transform the prepared tabular source data into a prompt friendly, semi contextualized format. While we might have forgone this step and just inserted tabular data directly, we felt we had better contextual control by unpacking the spreadsheets into sentences. We used simple bespoke Python scripts (Python was chosen for its familiarity and adaptability but any competent modern programming language might achieve the same effect). Standard Pandas (Python Data Analysis Library) routines were used to load the spreadsheets and then simple text manipulation methods such as *f* strings were used to turn the tabular data points into basic contextualized sentences suitable for later feeding to the LLM. This is illustrated in Figure 2.

In some tables there were multiple contexts present, such as a person’s occupation plus the extent of their land and stock holdings. In these instances, multiple independent fact sentences were created. The sentences, along with supporting information such as the date of the document and an individual’s unique identification number, were saved into a new database for later retrieval. We used a simple, single table MySQL database for this purpose primarily because of ease of implementation and tight integration with the Python platform. This process resulted in over 17,400 sentences, averaging five per person. With the sentences safely stored, a number of tasks were conducted. The first was to develop a prompt

Day	Month	Year	First name	surname	sentence	Crime	Lashes	Lashed pardoned	Remarks
20	November	1791	William	Walsh	800 lashes, wear iron collar on his legs and to have 5lb of flour week only	Detected of robbing a garden	93	707	No remarks

Contextualised sentences for the LLM

On the **20 of November 1791**, **William Walsh** was sentenced to **'800 lashes, wear iron collar on his legs and to have 5lb of flour week only'** for the crime of: **'Detected of robbing a garden'**. They received **93** lashes with **707** pardoned. The remarks on the punishment record stated: **'No remarks'**.

Figure 2. Example extract from the transcription spreadsheet and resulting sentences.

that resulted in a biography style output, utilizing the supplied context and data. For this phase we selected a single person's data as a constant along with a fixed context piece derived from sources such as the official government website about Norfolk Island (Department of Infrastructure 2023). We shall refer to this configuration from now on as our standardized person. The particular person chosen from our available options, Denis Mohair, was chosen because he was known to be well represented within our RAG datasets and would therefore provide us the opportunity to observe the AI operating without having to be concerned with the possible impacts of constrained inputs. The reality for many use cases however is that the available inputs are often limited (not every person mentioned in a tabular record will be well supported by supplemental RAG sources), thus potentially impacting both the length and quality of the outputs. Careful consideration should be given to the breadth of sources when planning any AI writing implementation, as those with primarily tabular sources and very limited RAG data might be better served by the much simpler regular expression sentence building method as described in the data preparation steps above.¹⁹

With the data and context fixed we varied the instructions in the prompt to observe the impacts. Initially, following some established guidelines, we created our own prompts from first principles. Largely this approach provided unsatisfactory results, with outputs either too short or too generalized to be useful (Zamfirescu-Pereira et al. 2023). Instead, we asked the LLM itself to provide us with a prompt template that would produce the outputs

we wanted. With some iterative testing and editing of the result provided by the LLM, the final prompt became:

Write a factual biography based on the life of {person}, who lived in the 1800's on Norfolk Island using the context and facts below. Include all the factual details about their life. Incorporate information from the facts and context about other people and places to ensure the biography is engaging, informative, and provides a comprehensive understanding of {person}. Facts: {facts} Context: On the 10th of October, 1774, Norfolk Island was claimed for the British Crown by Captain James Cook. Following orders from Governor Arthur Phillip, Lieutenant King was dispatched to take control of Norfolk Island, a mere six weeks after the First Fleet's arrival in Australia. On the 6th of March 1788, HMS Supply landed on Norfolk marking the beginning of the British Colony. This establishment was intended to secure the island and its resources, and to support the larger mainland settlement at Port Jackson. The island was fertile, leading to the creation of an agricultural settlement using convict labor. Those who couldn't fend for themselves were provided with food and occasionally clothing from government stores, a process known as victualing. By the early 19th century, many convicts whose sentences had expired and discharged marines opted to remain on the island. They accepted land grants, started families, and established their lives there. Around the same time, the larger colony of Port Jackson in Sydney was successfully founded. Colonization had also begun in Van Diemen's Land, leading to the decision to relocate convicts there instead of Norfolk. From 1807 to 1813, the population of Norfolk Island was moved to Van Diemen's Land. Convicts were integrated into the new colony's prison system, and the free population was given land grants. In 1814, the first phase of European occupation on Norfolk Island ended. To prevent utilization

by foreign powers the buildings were demolished and set ablaze and one of the smallest and most remote colonies in the British Empire was deserted.

While the results were now much closer to the desired output, it was at this point that many of the inherent biases within the LLM became apparent. These biases proved to be extremely interesting and instructive, albeit entirely recognizable and predictable. Key amongst them was the casting of the biographical information using the natural symbiosis of two populist, mainstream narratives (derived from the Web) which in our view, or at least for our tastes, played to the model's detriment. Both evoke what Craig Batty calls 'the physical and emotional threads of the archetypal hero's journey' (Batty 2010). The first pervasive narrative positions individuals primarily as characters who face then overcome adversity to find themselves in a better life situation. The second and related narrative is that of the stereotypical 'noble convict', which espouses the same trajectory but with a particular resonance for that more distinctive component of Australia's national genealogy—the criminal ('more sinned against than sinning') who suffers exile and servitude but is reformed to become a useful member of society (Roberts 2008). When the two stories meet in an LLM sense we can see people recast as victims of an unjust criminal system, living through the convict 'ordeal' before becoming the virtuous ancestor and progenitor of the national character.

The sentiments are well known to us; they are the core exculpatory and most marketable foundation myths of Australian national identity, traced eloquently in John Hirst's account of 'the Pioneer Legend' or, with respect to convict mythology, the 'popular taste' quantified by sociologists Bruce Tranter and Jed Donoghue (Bennett 1988; Tranter and Donoghue 2003). Their prevalence and perpetuation on the internet is maintained in no small part by convict-descendant societies and family researchers, who (as noted) are also the most likely audience of our research outputs. As professionals and critical thinkers however, we were less than satisfied with these results so attempts were made to eliminate (or at least quantify) their impacts.

To investigate the pervasiveness of these narratives in LLMs, we conducted an experiment on our standardized person which prefixed our standard prompt above with the following statements:

- Using a **positive** tone write a historical biography based on....
- Using a **neutral** tone write a historical biography based on....

- Using a **negative** tone write a historical biography based on....

Extracts of the results can be seen in the [Table 1](#).

Note the degrees of bias in the above results, most obvious in the positive and negative tone biographies which seek to disassociate the role of agency in the actions of the individual. Noticeably, in the negative results, the condemnation is applied to, or blamed on, a broader social and colonial milieu in which one is condemned by a cruel system, becoming trapped in a cycle of invisibility and deliberate neglect. In the positive mode the structural blame is just as implicit, however at least some encouraging personal lessons are arrived at. It is in this mode that the stereotypes are most pervasive, evoking the 'endurance of settlers', the spirit of 'cooperation' and their triumph over adversity in 'untamed lands'. They are qualities that contemporaries would not have ascribed to the convict Dennis Mohair, as explained below.

Interestingly, when the prompt instruction "Write a *factual biography*" is modified to read "Write a *historical biography*" the pervasiveness of the hero narrative becomes even more amplified, suggesting strongly that there is an inbuilt algorithmic association within the model between history and the hero story arc. This recalls the findings of Allison who has shown that writers of posthumous biographies (histories) frequently amplify the positive traits of their subjects (Allison et al. 2009). If this then is the pervasive style in general use, it helps to understand how this pattern has made its way into the LLM and highlights what we believe to be one of the current pitfalls in the use of AI in generating historical biographies.

Aside from altering the prompt, it is also possible to vary a number of model parameters programmatically. While there are many to choose from, one of the most impactful is the temperature (creativity setting) of the model. This parameter effectively weights the probability of a word appearing in a given sequence. If the temperature is low, the model returns the word combinations that are most commonly seen together (as per the training data). If the temperature is high, more statistically unlikely combinations will appear. Using our standardized person—the convict Dennis Mohair—we tried various model temperature settings. We found creativity values from 0 to 1 yielded useful outputs, and beyond that the usefulness of the output degraded quickly. For higher creativity values the outputs became increasingly unrealistic, with a tendency to draw conclusions from data that were not warranted, or manipulating the order of events to suit a counter-factual narrative. Consequently,

Table 1. Prompt tone results.²⁰

Negative	Neutral	Positive
<p>In the era where the unforgiving tides of history washed over the lives of many, Denis Mohair's story unfolded—a tale of dim endings and relentless afflictions of the soul. Born in an age of iron shackles and dire straits, Mohair's life, a canvas painted with the somber hues of hardship, was confined within the bounds of Norfolk Island, a speck of land first claimed for the British Crown by Captain James Cook in 1774.</p> <p>The foreboding journey to Norfolk Island began with ill-omened instructions from Governor Arthur Phillip. Lt King set sail, and the HMS Supply made landfall in March 1788, initiating the grim epoch of the British Colony. The island, although fertile, became a hellish paradise for the unfortunate souls sent to till its soil—convicts, bound by chains and suffering, coerced into labor under the guise of agricultural development.</p> <p>Amid this desolate setting, Denis Mohair emerged, a survivor of the Endeavor—a manifestation of the brutality of human destiny. With Leave, he remained on Norfolk Island, scraping by with the support of a settler. His existence there, however, is scarcely documented, a life seemingly unworthy of detailed chronicling in the eyes of those who held the pen. Denis Mohair, a convict, a mere footnote in the annals of history, was sustained, or rather, tolerated, through the act of victualing. The government begrudgingly provided food, and sometimes clothing, to individuals like him who were cast aside by fortune, unable to care for themselves in a world that expected nothing but endurance and labor in exchange for the most meager of rations.</p> <p>As the 1800s dawned and the community of Port Jackson in Sydney flourished, the once ignominious Norfolk Island convicts, such as Denis Mohair, found themselves relics of a bygone operational model. Van Diemen's Land was now the favored destination for Britain's unwanted, and from 1807 to 1813, the transfer of Norfolk's population ensued. Those like Mohair, who once saw the island as a final vestige of hope, were now swept into the new colony's prison system, while free settlers received land grants—a reward that would forever elude the grasp of individuals like Mohair.</p> <p>The sunset of Norfolk Island's occupancy was marked not with grace but with destruction. In 1814, the island's abandonment was ensured through acts of annihilation: buildings were razed, livestock slaughtered, and the brief chapter of one of the smallest, most remote colonies in the British Empire was concluded in ash and silence.</p> <p>The ignoble end for Denis Mohair came not through oblivion but by the gallows. On the 2nd of May 1796, the harsh finality of a noose brought the tale of this male convict to a close. No lofty prose colored the document that scribed his demise—no remarks, no commemorations. In the vicious ledger of the colony, Denis Mohair was nothing more than a statistic, his death a mere procedural entry in a bureaucratic record.</p> <p>His biography, drenched in the bitterness of his era, is a reflection of the cruelty of a colonial system that chewed up the lives of the disenfranchised. Denis Mohair, now extinguished, lies as a testament to the despair and the relentless grind of an empire that saw men as expendable assets—a tragic embodiment of countless others whose breaths were snuffed out quietly on the periphery of the great British narrative.</p>	<p>Denis Mohair, whose life unfolded during the tumultuous era of penal colonies and exploration in the late 18th and early 19th centuries, became a footnote in the history of Norfolk Island, an outpost in the Pacific Ocean claimed for the British Crown by Captain James Cook on October 10, 1774. The story of Denis Mohair is one emblazoned with the harsh realities faced by the convicts of that time, and yet it remains largely untold, save for a few stark facts that narrate a life lived at the edge of the world.</p> <p>Norfolk Island, a small, lush landmass, was set in the wide expanse of ocean with tall pines and fertile grounds that belied its future as a place of punishment and ultimate desolation for many. Governor Arthur Phillip, recognizing the island's potential for providing resources and relieving the burden on the nascent colony at Port Jackson, dispatched Lt King to secure possession of the island. The HMS Supply, arriving in March 1788, marked the island's transition into a British colony. Its initially rich soil and the introduction of convict labor turned Norfolk Island into an agricultural hub, providing support for the larger settlement on the Australian mainland.</p> <p>As the nineteenth century dawned, the penal settlement on Norfolk Island had undergone significant changes. Many convicts, having served their sentences, and discharged marines chose not to return to Britain or the ever-growing colony in Port Jackson but to stay and make a life on the island. These early settlers received land grants, which they cultivated, and started families, creating a community that was as robust as it was remote.</p> <p>Denis Mohair was among those who found themselves forging a life on Norfolk Island during this period. A convict, Mohair arrived under circumstances that remain opaque, his life prior to this a blank slate in the historical records. However, it is known that after the Endeavor, he remained on the island with official leave, suggesting he had served his sentence or otherwise earned the right to stay. In the nascent and isolated community, Mohair was supported by a settler, indicating some degree of integration into the fabric of island society. Yet, Mohair's story took a tragic turn. On the 2nd of May, 1796, he met his end by execution. The reasons for his execution are lost to history, as no remarks are noted in the surviving document that records his death. His status, simply "male convict," and the date of his demise are the scant details left to mark the conclusion of a life caught between the unforgiving discipline of a penal colony and the faint hopes of freedom that Norfolk Island must have once represented.</p> <p>By the time of Denis Mohair's death, the future of Norfolk Island was already uncertain. As the larger colony of Port Jackson thrived and Van Diemen's Land began to receive convicts, Norfolk's strategic value waned. The difficult decision was made to dissolve the island settlement, with its population transferred and its buildings, records, and the everyday marks of its inhabitants' lives obliterated. In 1814, the settlement was abandoned, the livestock killed, and the remnants of the colony destroyed.</p> <p>In the vast tableau of history, individuals like Denis Mohair often become overshadowed by the grand narratives of colonization and empire. Yet, his life and death are testament to the countless personal stories that played out in these far-flung corners of the world, each one contributing to the complex tapestry of our shared past. Though his life details are scarce, Denis Mohair's presence on Norfolk Island serves as a reminder of the human element within the broader context of historical events, a life once lived on a small island that briefly played a role on the global stage.</p>	<p>Denis Mohair, a man whose name is quietly etched in the annals of Norfolk Island's early settler history, led a life that embodies both the hardships and the spirit of perseverance that were hallmarks of the era. Born in a period defined by exploration and colonial expansion, Denis's journey intersected with pivotal moments of British seafaring history, including the remarkable voyages of the HMS Endeavor.</p> <p>Though much of Denis's early life remains shrouded in the mists of time, it is known that his fate became entwined with Norfolk Island's story following the island's sighting by the esteemed Captain James Cook in October 1774. As Britain sought to solidify its claims in the far-flung corners of the globe, Norfolk Island emerged as a jewel in the crown of the British Empire due to its strategic location and bountiful resources. Under the directive of Governor Arthur Phillip, the British sought not only to claim this land but to cultivate it. In March 1788, scarcely after the establishment of the colony at Port Jackson, the HMS Supply carried Lieutenant King to Norfolk Island's lush shores, setting in motion the creation of a burgeoning agricultural outpost.</p> <p>It was within this context of growth and colonization that Denis Mohair found himself on Norfolk Island. By the early 1800s, the island had transformed into a place where many, including former convicts and discharged marines, chose to lay down roots, embodying the spirit of resilience and adaptability.</p> <p>Denis, having survived the journey on the HMS Endeavor, was a male convict whose subsequent life on Norfolk Island was marked by the support he received from a settler. While specific details of his relationship with the settler or the nature of his daily life remain largely unspecified, what is clear is that Denis was integrated into the island's community—a testament to the cooperative spirit that often emerged in such remote settlements.</p> <p>In time, the tides of history turned and the decision was made to transfer Norfolk Island's population to Van Diemen's Land. Convicts were woven into the fabric of the new colony's prison system, and the free population received land grants as incentives for relocation. This mass migration marked the end of an era for Norfolk Island, with the colony all but abandoned by 1814. The dismantling and burning of buildings and the eradication of livestock left the island as a ghost of its former self.</p> <p>Tragically, Denis Mohair's life came to an untimely end prior to the mass exodus from the island. On the 2nd of May, 1796, he was executed—the reasons for which are not recorded, leaving one to only ponder the circumstances that led to this grave outcome. No further remarks are made on the historical document concerning his death.</p> <p>Despite the brevity of detail on Denis Mohair's life and the somber note on which it concluded, his existence is a thread in the fabric of a larger narrative. His life on Norfolk Island serves as a reminder of the early settlers' endurance, the complex legacy of colonial expansion, and the lives, often unremembered upon, that played roles in the shaping of distant outposts of empires. Denis Mohair, like many of his contemporaries, lived in an age of bold ventures and new horizons, his story echoing the enduring human themes of survival, community, and the quest for a place to call home amidst the vast oceans and untamed lands of our world.</p>

a setting of 1.0 is recommended as a useful reference point, although that value should be approached with some caution. We note also that our experience with temperature settings are only valid for the LLM that we used, in the context that we used it, so some personal experimentation is needed in other use cases.

The final piece of the puzzle, and key to improving the effective AI use for comprehensive biographies, involves inserting a variable context into the prompt, utilizing the RAG model. Before discussing this however, it is useful to return to what else we know about our selected test subject. Dennis Mohair appears in our tabular Norfolk Island dataset *via* three documents only, all in a single year, first appearing after he survived the shipwreck of the ship *Endeavor* in Dusky Sound, New Zealand in October 1795. We know that he and other rescued convict survivors were transhipped to Norfolk Island and were ‘supported’ (presumably employed) by local but unnamed settlers. He subsequently appears in a ‘victualing’ book of rations issued by the state. And then, his most distinctive contribution to the Norfolk Island story, he was executed on the Island, although our spreadsheets provide no further explanation or context for that event. We also know from official correspondence that Dennis Mohair’s story is larger and much richer than is captured in our spreadsheets. For example, we know that Mohair was a Dubliner, was likely a stow-away on *Endeavor*, and that he arrived on the Island in a deplorable condition. His execution, the first ever on Norfolk Island, was for a brazen and very ugly act of burglary that was related in detail by the Lt Governor, who also described how Mohair ‘suffered with much contrition and a thorough sense of his guilt’ when led to the scaffold. These are pivotal biographical fragments, relished by human biographers, that are not only unknown to the AI in the examples above, but are substituted with low value or irrelevant content, an issue that we sought to overcome using the RAG methodology.

As an initial test, we alerted our model to these additional sources and facts concerning Dennis Mohair. The intention for this was twofold; first, was to fill holes in the *capta* data model to create richer biographies, and second, was to try and use context to reduce the prevalence of the hero story arc by ensuring facts that would be counter to that trajectory would be present in the context (like finer details and the flavor of an eyewitness account). In this testing the first objective was partially met, the second was not.

To understand how the first objective was approached it is useful to return to the concept of data and *capta*. Data for our context is any

information that has been collected about a person, place, event or thing. *Capta* in this scenario is data that has been captured with a very specific purpose in mind. It is important to make this distinction because the information in the Norfolk Island tabular data set is *capta*. It has been captured with a very specific intent. In fact, for our data set, around 50% of the captured data was generated by the colonial administration for the purposes of ensuring the inhabitants of the island could be correctly fed (either through public victualing or private means) and contains little or no further contextual material. The importance of this is not so much what is captured *per se*, but what is *not* captured. Information collected for the express purpose of ensuring people remain nourished and fed has little or no concern with their current and past behaviors, the current social conditions or what their lived experience might be. We propose that the solution is to acknowledge that Norfolk Island tabular datasets represent a closed system with known blind spots and to use automated processes across a wide arc of curated supplementary sources (like letters and diaries) to fill these gaps.

Computationally, the process of adding context is relatively straight forward and uses well accepted RAG principles. In this RAG process, supporting information (freeform text, additional tabular data etc.) are placed in a vector database, usually in data chunks that are around 1000 characters in length, often with a buffer window (snippets of the preceding and following chunks added to maintain continuity) of around 100 characters. The vector database itself (in our case the Chroma platform),²¹ stores those text chunks alongside a numerical vector representation. These vectors are generated by algorithms that consider the relationships between words in a sentence or group of sentences. When searching a vector database, the desired search terms are turned into numerical representations and then mathematically compared to those in the database. The records in the database with the closest mathematical match represent the word sequences that have the closest semantic similarity to the search term. How similar the results are to the search term can be determined by the user, with results typically ranked by closeness (mathematical and therefore semantic similarity). By adjusting the closeness cut off to a broad setting, it is possible to return even loosely related content. This has the effect of returning results for many of the noun groups in the source text (anything related to the people, places or things present in the text) which in turn provides the most comprehensive set of possible results. These can then be absorbed or discarded as necessary.

For the context generating routine used in this paper, this lookup process is sequentially repeated, with each set of returned information forming the basis for the next search. The process begins with the sentence-formatted facts for the person, derived from the Norfolk Island capta. This information is fed to the vector database and a broad set of returned results are then concatenated together to form a new data block. The block is deconstructed into sentences and then fed back into the context generation loop so that the database now looks for information that may support the previously returned context, such as additional information about newly mentioned people or places. This process could be repeated as many times as desired, but for our purposes we used a double loop, excluding any previously returned blocks and with tight relevancy thresholds to provide context without overloading the prompt with increasingly distant or repeated facts.

It is worth noting that there is an inherent risk of retrieving incorrect information with this approach, especially when the RAG database is very large and potentially contains many people with the same name or with few distinguishing textual features. This is partially mitigated for us by only accepting results with high relevancy scores (multiple matching

elements), however it does not remove it completely. A more intelligent approach would be to couple the RAG retrieval to a knowledge graph to ensure the relevance of supporting information.²² Whilst we have written elsewhere about our creation and use of knowledge graphs for Australian colonial history, a detailed coverage of the integration of RAG and knowledge graphs is out of scope for this paper.

Assessing the impacts of RAG

To better understand the impacts of the RAG process, and how the AI model responded to RAG input, we devised a small experiment. We sourced (with permission) twenty previously written and fully referenced biographies of Norfolk Island residents, researched and published by Cathleen Dunn, a highly regarded author and long-time history and heritage consultant with a well-recognized expertise in early Norfolk Island history (Dunn 2015a; Dunn 2015b; Dunn 2016; Dunn 2022a; Dunn 2022b). These biographies were randomly selected and varied in length and detail. Of the 20 samples, the minimum word count was 148 words, the maximum was 704 words and the mean was 324.5 (Figure 3).

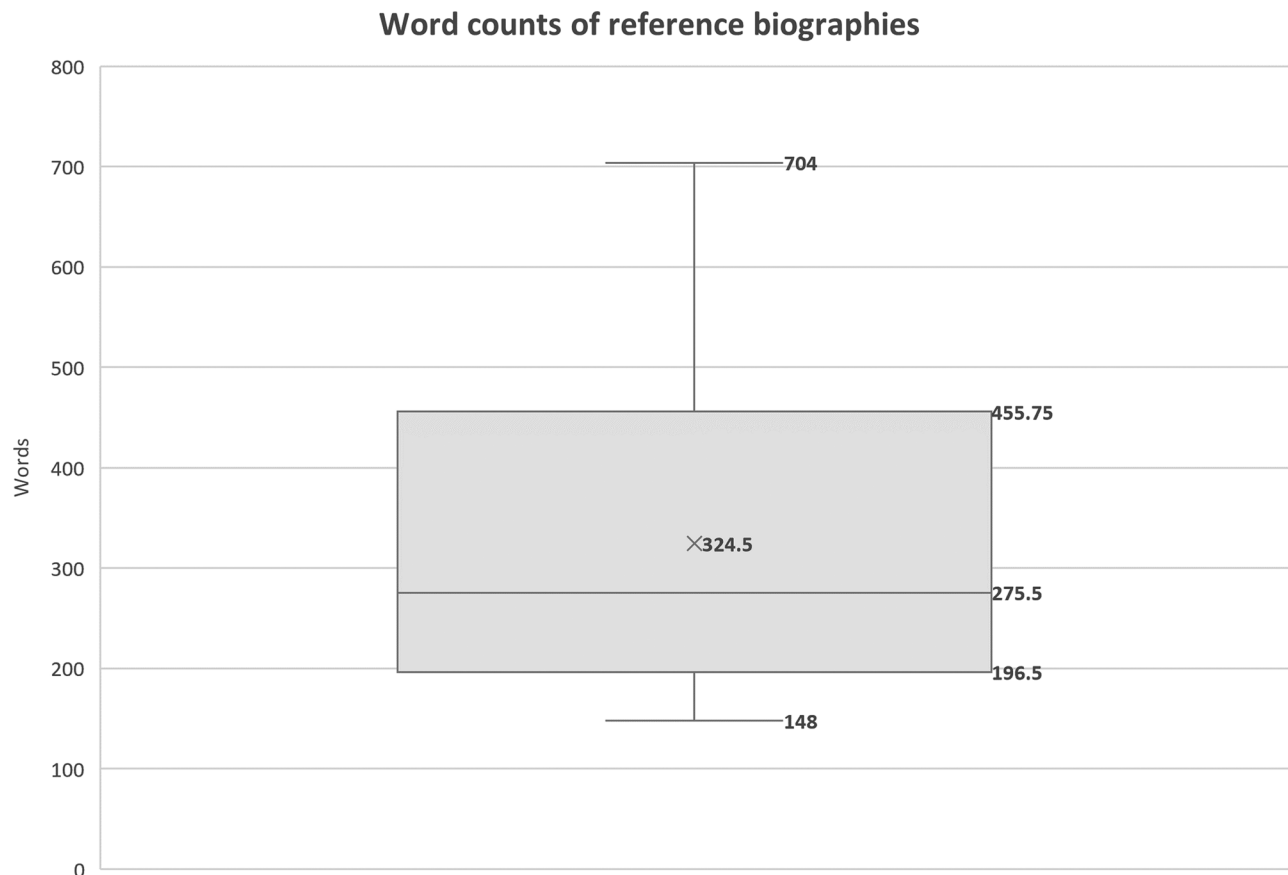


Figure 3. Box plot of the word counts of the reference biographies. (Min, Q1, Median, Mean, Q3, Max).

For our testing, we created a specific RAG database containing all the information from the source biographies. The data was loaded into the RAG database as a singular data bundle per person (not split across multiple entries as is often used in RAG approaches), thus ensuring that any match for a person would return the full biography for that person. With this setup in place, we used a single loop RAG process to generate AI biographies for every person in our test RAG database. The results of the generated biographies were then compared against the originals to detect omitted, incorrectly contextualized and hallucinated information. The results of the tests can be seen in [Table 2](#).

In order of increasing magnitude, we detected two instances of model hallucination, where the model simply invented data. We also detected 11 instances where the model misunderstood the context of the facts, thereby changing their meaning. By way of example, in our testing the following output was generated:

Abraham Lee, originally known as Charles Lee, was a convict who lived in the 1800s on Norfolk Island... 'The lives of Abraham Lee and Elizabeth Youngson intertwined in the complex social fabric of Norfolk Island and Sydney during the 1800s.

However, in the supplied RAG data, Lee was never on Norfolk Island. Rather, he had a brief marriage to Elizabeth Youngson (a one-time resident of Norfolk) while she was in Sydney on the mainland, New South Wales. Additionally, Elizabeth departed Norfolk Island in 1794, hence the statement around the social fabric of the 1800s misrepresents reality.

The most striking result from the test however is the number of facts present in the RAG data that did not make their way into the output, with 243 instances detected. The majority of these omissions were an artifact of source data summarization, where key elements of information (such as specific dates, court references, personal details etc.) were discarded to fit into a higher-level narrative, examples of which can be seen in [Table 3](#). We detected no examples where all the facts in the RAG data were fully represented in the output. This tendency to summarize has some serious implications for our style of work. Dates and references are critical aspects of constructing and

Table 2. Results of RAG testing.

Facts present in the source, not in the output (ignored facts)	Hallucinated facts (made up)	Misrepresented/context shifted facts
243	2	11

interpreting context, so whilst we would still commend the use of RAG as an efficient way to provide the AI model with additional information, we would also caution users to be wary of its limitations ([Figure 4](#)).

Production use of RAG

For our work, we gave the RAG system access to around 400 Mega Bytes of our previously collected and collated research materials about Norfolk Island including verified transcripts of convict transportation records, court documents and various first-hand accounts such as letters and diaries. The results from this expanded context were immediately discernible and the output below provides an example of AI output using RAG enhanced context for our test subject, the convict Dennis Mohair.

AI output using RAG

Denis Mohair’s life on Norfolk Island in the late 18th century is emblematic of the complex and often harrowing experiences of the convicts who were sent to the far reaches of the British Empire during that era. Born into a world that offered little in the way of mercy for those who ran afoul of the law, Denis’s

Table 3. Examples of RAG data omitted by the AI model. Missing elements bolded and italicized for emphasis.

RAG Data	AI Output
Children of Elizabeth Pipkin: 1. Child PIPKIN, born 1790 Norfolk Island, died 1 December 1790 "a child belonging to Elizabeth Pipkin died today - it is a good thing that it is dead poor thing for the mother took no care (care) of it"	Elizabeth’s life took a tragic turn with the birth and subsequent death of her children on Norfolk Island. Her child born in 1790 passed away, with accounts suggesting neglect on Elizabeth’s part. Another child, Catherine, born in 1793, also tragically died shortly after birth.
2. Catherine PIPKIN, born November 1793 Norfolk Island, died 1 February 1794 Norfolk Island.'	
Crime: Break, Enter and Steal - breaking into a warehouse and stealing money of 41 shillings in silver and six shillings and nine pence in copper with her brother George Youngson. Tried: Lancaster 26 March 1787. Sentence: Death commuted to 7 years transportation.	In 1787, Elizabeth, along with her brother George, committed a crime of breaking into a warehouse and stealing money. They were tried in Lancaster in March 1787, with Elizabeth’s death sentence commuted to 7 years of transportation to Australia.
Mrs Ann STEEL, Convict, Lady Juliana 1790. Born: c1762. Crime: Highway Robbery. Tried: Middlesex, 12 September 1787. Sentence: Death. In April 1788 her death sentence was reprieved to transportation for Life. Ann arrived on Norfolk Island aboard the Surprise in August 1790.	On the island, James formed a relationship with Ann Steel, a convict who had been sentenced to death for highway robbery in Middlesex. Luckily, her sentence was commuted to transportation for life, and she arrived on Norfolk Island in August 1790.

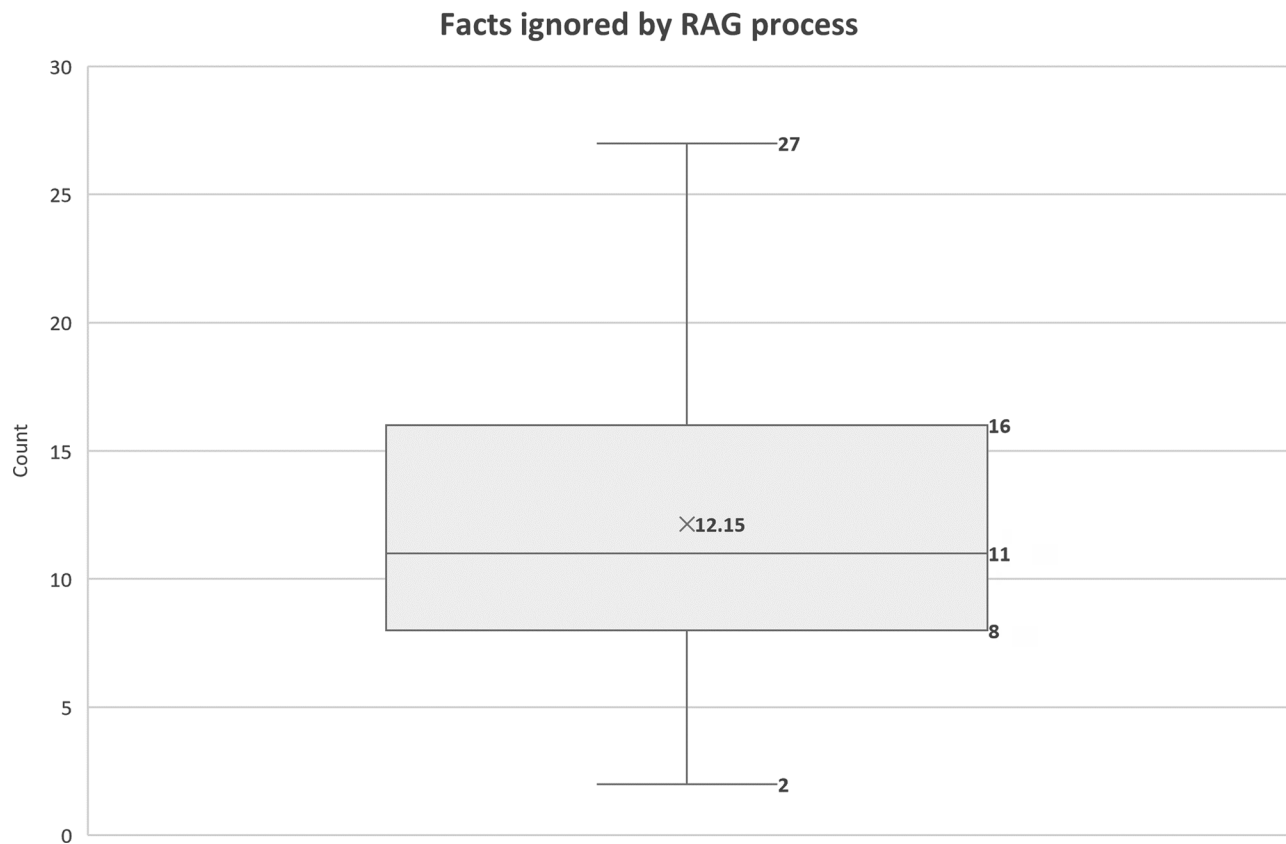


Figure 4. Box plot of number of facts present in the supplied RAG data, not present in the output. (Min, Q1, Median, Mean, Q3, Max).

trajectory was forever altered when he became entwined with the criminal justice system of his time.

The backdrop for Denis Mohair's later life was set with the sighting of Norfolk Island by Captain James Cook in 1774, and the subsequent establishment of a British colony there in March 1788. The island was selected to serve as a source of resources and agricultural support for the larger colony at Port Jackson. Convict labor was central to this endeavor. Norfolk Island, with its fertile lands, stood as a stark contrast to the harsh conditions and crowded cells from which its involuntary settlers came.

By the turn of the 19th century, Norfolk Island had begun to transform. Some convicts, having served their sentences, along with discharged marines, chose to remain, taking advantage of land grants and the opportunity to build a new life away from the past that branded them. This was the world Denis Mohair, a male convict, came to know—a world that offered a glimmer of hope in the form of support from settlers and a chance at redemption.

However, Denis's life took a turn for the worse with a series of events that would see him remembered more for infamy than for any attempt at reforming his life. Reports from the time indicate that Norfolk Island, once a more peaceful settlement, saw a resurgence in criminal activity following the arrival of a

group of convicts from Port Jackson on the ship named Supply. Denis, a survivor of the Endeavour and part of the criminal element that preceded the Supply, became embroiled in the fray.

In a testament to the desperation and perhaps the moral corrosion that life on the edges of civilization can cause, Denis, along with his accomplices, committed a series of robberies that shook the small community. One of these crimes, a burglary, was marked not only by theft but by a cruel disregard for human decency, as a miller and his wife were bound and terrorized while the perpetrators made off with money and goods.

Eventually, a combination of reward offers and the incentive of a pardon led to the unravelling of the gang's activities. The web of justice that caught Denis Mohair was spun from the testimony of a gang member, who turned evidence against his companions in exchange for leniency. This evidence painted a clear picture of guilt, leading to the unanimous conviction of Denis and his co-conspirators by the criminal court.

The severity of the crimes called for an equally severe example to be made. The first execution to take place on Norfolk Island was ordained for Denis Mohair, serving as a dire warning against future crimes. His fellow culprits were spared the ultimate punishment

under specific conditions, but for Denis, there would be no reprieve.

On the evening of May 2, 1796, Denis Mohair faced his fate. His end came with a stated contrition and a palpable sense of guilt for the crimes he had committed. The absence of a clergyman to provide spiritual guidance in his final moments was a matter of regret, but the dire need to set an example overruled this concern. It was hoped that this grim spectacle would resonate within the community, deterring others from following a similar path of crime and thus avoiding the need for further executions.

Denis Mohair's story, punctuated by his execution, draws to a close a chapter in the early history of Norfolk Island, reflecting the harsh realities of a penal colony and the lives of those who, willingly or not, played a part in its story. His legacy, logged tersely into the official records without remarks, leaves us with a window into the struggles and the ultimate downfall of a man caught in the gears of a punitive colonial system.

Aligned with the results from our RAG testing we found a high level of congruency between the source data and the resulting text (that is, no invented data). However, once again we found that not all information presented in the source facts or context made it into the final output, even though the AI prompt specifically instructs it to include all data.

With regards to our second objective of tuning out bias *via* extended context, we found this approach to be highly ineffectual for the AI models that we used. Despite best efforts, including experimenting with direct injection of deliberately constructed contentious sentences, we were unable to overcome the general tendency of the AI to try and position people positively and to shift responsibility for personal actions away from the individual and toward (assumed) prevailing social systems. By way of very simple reinforcement, eleven of the twenty biographies generated during our RAG testing process contained the word 'resilience', despite this word being completely absent from the source RAG data and prompt. Whether or not this holds for AI models from other providers is unclear. However, a casual test using the open source GPT4ALL Falcon Model using the same inputs showed the same tendency to emphasize the positives, suggesting that positivity bias should be carefully considered regardless of the model provider.²³

Conclusion

We have shown that AI has the potential to change the way that historians utilize both tabular data and other unprocessed sources such as diaries, letters and

other primary accounts. By using computational methods, we have demonstrated that it is possible to transform the tabular into the biographical, particularly when the data pool available to AI is properly curated and sufficiently wide. We have shown, however, that at various stages of the process, manual human labor and input remains preferred and vital. Following Janie Solberg's (2012) warning, over a decade ago, the use of technology may never entirely exonerate us from certain time-honored forms of research labor.

We have nonetheless demonstrated that it is now feasible to use AI as a shortcut to producing narrative text from spreadsheets. Given enough data and context, AI has shown that it is capable of drawing out the individual from the numbers and generating a plausible life course description, albeit with some notable limitations. In particular, we have shown that, with the technology as it currently stands, AI has an undesirable tendency to trend toward a positively biased output when discussing life courses, diminishing critical perspectives in favor of narratives that espouse personal triumph over systematic adversity. This was especially problematic in the case of our subjects, who were mostly convict exiles whose criminality is circumvented and whitewashed in nationalistic mythmaking.

Additionally, we find an unhealthy tendency for AI to summarize and discard information that is critical to historical narratives and to occasionally misinterpret context. Consequently, in our quest for legible, intelligent and reliable computer driven biographies we find AI lacking on the last two counts. For this reason, we conclude that AI, like many computational tools, should be considered for their utility as part of a comprehensive inquiry chain, not as a wholesale replacement of the chain itself. We have used machines to resurrect ghosts, in the form of short encyclopedic-style accounts of individual lives. While LLMs accomplished what we intended, these canned outputs, more descriptive than analytical, are of course poor substitutes for the products of the very human literary endeavor of writing biography. To paraphrase Jon Chun and Katherine Elkins (2023), we still have some way to go before we have programmed our humanity into AI.

Notes

1. For an introductory overview on Australian innovations on the use of big data, see Maxwell-Stewart (2016) and Maxwell-Stewart, Roberts, and McLean (2023).
2. In our own research area, see especially Tuffin et al. (2018).

3. On the theories and challenges of Digital Cultural Heritage, see for example, Cameron (2021).
4. There are books for the years 1788, 1792 to 1796, for 1802 and 1803, and then for every six month-period until March 1810, too numerous to list here but see for example, Norfolk Island Victualling Book, 1792–1796, SAFE/A 1958 (Safe 1/266), State Library New South Wales, Sydney. Other books for the early 1800s are in the Colonial Office (CO) series in The National Archives (TNA), Norfolk Island Victualling Book, 1 January to 31 December 1802, CO201-029, ff. 211–225, TNA. See also Norfolk Island Victualling Book, July to December 1806, 4/1167B, ff.293–312, and July to December 1807, 4/1168a, ff. 431–445, in State Records New South Wales (SANSW). There are no surviving books for the years 1797–1801.
5. For example, A List of every man, woman and child on and off the Stores residing at Norfolk February 1805, 4/1167a, ff.260–270, SANSW; Muster of Settlers & Land Holders on Norfolk Island, 2 August 1807, CO201-044, ff. 293–297, TNA.
6. Especially Reg Wright's remarkable 'List of Residents of Norfolk Island 1788–1814' included in Nobbs (1998). See also Donohoe (1986).
7. For example, Royal Navy Ships Musters, Porpoise, Supernumeraries, Port Jackson to Norfolk Island, February 1801, ADM36-15448, ff. 129–131. These records are now available online via the National Library of Australia <<https://nla.gov.au/nla.obj-732027610/findingaid?digitised=y>> (13 December 2023).
8. This component of the database is available at <<https://hdl.handle.net/1959.11/57760>> (D. A. Roberts 2024).
9. For some benefits of recreating colonial populations see Rowse (2017).
10. See Maxwell-Stewart (1999).
11. On the trajectory of the historiography, especially its concern for the moral character of Australia's founding population, see Roberts (2011).
12. See especially, but far from exclusively Godfrey et al. (2021) and Finnane, Kaladelfos, and Piper (2018).
13. On the use of other off-the-shelf tools, see Monroe et al. (2022). For the promising use of AI in this space see Dahl et al. (2023).
14. Although, there is some confidence that these risks can be countered to restore a 'moral direction' to modern LLMs. See Schramowski et al. (2022).
15. For further reading on the topic see Swire-Thompson and Lazer (2020).
16. Discussed recently in Donker (2023).
17. For examples see Topsakal and Akinci (2023).
18. OpenAI. (2003). gpt-4-1106-preview API. Available at: <https://platform.openai.com/docs/models>.
19. We note that maintaining comprehensive rule sets to account for widely varying input data using regular expressions can be an onerous task. Therefore, data quality should be prioritized if this approach is selected.
20. Authors note: early experiments using the same prompt with the 3.5 Turbo model produced even more blatant results, indicating that the continuous improvement cycle of the developers is helping to whittle down these issues.
21. <https://www.trychroma.com/>.
22. For current thinking on the topic see amongst others: Edge et al. (2024).
23. The Falcon model also showed a slightly reduced tendency to comment on social circumstances but was hampered by a distinct tendency to hallucinate, creating names, relationships, ages and dates not present in the supplied facts or context, making the biographies highly inaccurate.

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