Correlations between gender and research topics at three major archaeology conferences

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Text of abstract

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# 1 Abstract

Disproportionate representation of genders has long existed in many academic fields. Rising interest in gender equality in society generally has resulted in greater scrutiny on gender inequality in academic communities. Analysis of authorship of peer-reviewed publications shows that archaeology is similar to other academic fields in having long been dominated by men. We ask if gender disproportionality is evident in the choice of topics that archaeologists present on at major conferences, particularly the Society of American Archaeology (SAA), the European Association of Archaeologists (EAA) and the Computer Applications and Quantitative Methods in Archaeology (CAA) meetings. Does the gender of the participants in these archaeological conferences correlate with the topics of their presentations? We analysed presenters’ names in the published programs of these three archaeology conferences to infer gender. We then used machine learning to identify topics from presentation titles. We found that there are some associations between gender and topics. An awareness of these correlations between research topics and gender is important to ensure equitable participation in archaeology, and unbiased access to training opportunities for students. We expect these findings to be useful for instructors who prioritize gender equality in student and early career research activities.

# 2 Introduction

Gender under-representation and inequality has long existed in science, from under-representation of women and minority genders in school text books to academic publications (Hamilton et al., 2006; Tushingham et al., 2017). Women are often under-represented for several reasons, including stereotyping that unfairly underestimates individuals’ abilities, which often leads to lack of support for women in academic fields (Xu, 2008). Although the gender gap in academia has been shrinking in recent years, there remain substantial differences, which often result in underrepresentation of women in many fields and career stages, as well as disadvantages such as lower salaries and less access to high-prestige employment (Caprile et al., 2012). Even research into these gender biases suffers a bias, with Cislak et al. (2018) finding that articles on gender bias and race bias are funded less often and published in journals with a lower Impact Factor than articles on comparable instances of social discrimination. In this paper we explore the relationship between gender and archaeological research topics to determine if women and men tend to focus more on certain topics than others.

We used a computational method to identify topics from the titles of presentations delivered at meetings of the Society of American Archaeology (SAA, 2018), the European Association of Archaeologists (EAA, 2018) and the Computer Applications and Quantitative Methods in Archaeology (CAA, 2018). We analysed the covariance of topics and genders of presenters to explore how gender ratios vary between these conferences and by topics.

# 3 Background

Gender bias and imbalance has been a concern in archaeology since the earliest discussions of the social structure of the discipline (Gero, 1983). According to the American Anthropological Association’s (AAA) *AnthroGuide*, there is a growing number of women participating in anthropology’s graduate programs. For example, in the 2012-2013 school year, women consist of 64% of graduate students in anthropology programs and 65% of students that completed an anthropology doctoral degrees were women, whereas in 1972 32% of PhD are granted to women and 59% in 1995 (Bardolph, 2014). Although women slightly outnumber men in anthropology graduate programs, previous work has shown substantial gender imbalances in publication practices in archaeology where men greatly outnumber women, especially as first authors in peer reviewed journal articles (Bardolph, 2014). One of the first studies of this imbalance in publication practices is Bardolph (2014), who looked at 7,381 members of the Society of American Archaeology and found 53% men and 47% women. She also looked at 1,601 articles published during 1990-2013 in five high-visibility archaeology journals and found a range of proportions of women to men authors of 0.32-0.73, with three of the five journals having a proportion of <0.5.

Rodrı́guez-Álvarez and Lozano (2018) studied gender balance among 309 authors of 299 publications produced during 1978-2016 by the Atapuerca Project, a large archaeo-palaeontological project in Burgos, Spain. They ‘manually defined’ the gender of each author, and found 13 articles authored exclusively by women, 34.8% of papers have women as first-authors, and overall, 35.9% of all authors are women (Rodrı́guez-Álvarez and Lozano, 2018). Over time, they observed a trend of increasing numbers of papers that include women as authors, numbers of paper lead by women as the first author, and increases in the ratio of female to male authors in group-authored papers. They did not make any observations about relationships between gender and topics.

Another similar imbalance can be seen in terms of the authorship of articles or papers written. For example, for the authorship of the first authors of 1,104 articles published in the *Journal of Field Archaeology* during 1974–2018, 72% of them are men (Heath-Stout, 2020). Heath-Stout (2020) investigates the possibility that the gender gap in authorship is due to due to sexism in the peer review process. Out of 830 instances of peer review for where both the reviewer’s gender and the first author’s gender could be determined, neither the first author’s gender, the reviewer’s gender, nor the combination of the two had a significant effect on the reviewer’s recommendation.

Fulkerson and Tushingham (2019) collected data on author’s gender and occupational affiliation in peer reviewed journals (*American Antiquity* (AQ), *Advances in Archaeological Practice* (AAP), *Journal of California and Great Basin Anthropology* (JCGBA), and *California Archaeology* (CA)) and some non-peer-reviewed venues (the *SAA Archaeological Record* (SAA Record) and the SCA *Proceedings*). Among the 5,010 authors of 2,445 articles in their sample, 27.1% of first/single authors of peer-reviewed journal articles are women, and 72.9% are men. The gender gap is less pronounced in the non-peer-reviewed venues with women accounting for 40.8% of lead authors in 517 articles.

Bardolph (2018) examined data from 2007 to 2017 about the membership in the Society of California Archaeology (SCA) conference, and the lead-authors of JCGBA and CA. Bardolph (2018) noted that women’s conference presentation rates are consistent with their membership rates in SCA, and that it was not until 2017 when women’s participation rates finally exceeded men’s. Although women are more actively participating in SCA, this is not the case for lead-authorship of JCGBA and CA (Bardolph, 2018). Throughout the majority of time in the period studied, lead-authorship of JCGBA articles is highly skewed towards men with only 34% women. A greater difference between men and women lead-authorship can be seen in CA, in 2009 there was no women lead-authors at all, and overall only 23% of the published papers of CA have women as lead-authors (Bardolph, 2018).

When looking at gender ratios among the membership in Society for California Archaeology from 1967 to 2016, Tushingham et al. (2017) report a trend of women increasingly maintaining their society membership they remain underrepresented in peer-reviewed journals. Tushingham et al. (2017) examined authorship gender trends in 1,599 papers in three journals, *Journal of California and Great Basin Anthropology/Journal of California Archaeology* (JCGBA/JCA), *California Archaeology* (CA) and a non-peer reviewed *Proceedings* of the Society for California Archaeology (PSCA). In a total of 2,617 authors, 844 (32.3%) were women, 1,762 (67.3%) were men, and 11 (0.4%) were gender unknown/ambiguous (Tushingham et al., 2017). They found significant increases in the proportion of female lead authors over time in JCGBA/JCA and PSCA, but not in CA, perhaps because of the shorter publishing period for this journal (Tushingham et al., 2017). This similar trend of a gender gap in archaeology can also be seen in women’s pay (VanDerwarker et al., 2018). In the University of California, Santa Barbara Gender Equity Project,(**vanderwarker2018uscb?**) report an imbalance in pay rates, for example, women make a greater proportion of people paid less $60,000 and men outnumber women in salary brackets greater than $60,000. (**vanderwarker2018uscb?**).

Studies of authorship where gender is inferred from the author’s first name are common, but can give wrong results for non-English, androgynous, and uncommon names. Heath-Stout (n.d.) avoided these limitations by conducting a survey that directly asked archaeologists for their self-identifications of gender, race/ethnicity and sexual orientation. In her intersectional study, Heath-Stout (n.d.) found a higher number of women publishing in archaeology than shown in previous studies, even in the studies of the same publications that she studied. Heath-Stout (n.d.) explains this as a result of change over time, with her study including more recent publications than others, and concludes that most journals is slowly reaching gender parity.

Sinclair (2016), compared the relative standings between men and women researchers in terms of number of citations made by other authors in the field of archaeology. Among the list of 50 most cited authors, only 6 of them (12%) are women, meaning that recognition by citation is still mostly given to men. A similar result can be seen if we increase the sample to the top 250 authors, with 19% women (Sinclair, 2016). After analyzing the most cited authors and their articles’ thematic clusterings, they found that there are relatively more women authors in the category of archaeology of early state societies in the Americas (N and C America) with 46% women authors. Other categories with high proportions of women are archaeological chemistry (esp. lipids analysis) with 40% women authors, Isotope analysis with 30% women authors, and dating (esp. thermoluminescence and magnetics) with 30% women authors. The average women author cited in the field of archaeology as a whole is around 14%. Sinclair concludes that the higher representation of women as cited authors on topics of laboratory analysis supports Gero’s (1994) claim that women in archaeology were most active in laboratory-based activities rather than excavation/fieldwork related activities.

In this paper we advance the study of gender and authorship in archaeology by specifically focusing on the gender imbalance that occurs in the topics that the authors present in major archaeological conferences.

# 4 Methods

We requested from conference organisers spreadsheets files of the publicly available program information for three major archaeology meetings held in 2018: the Society of American Archaeology (SAA), the European Association of Archaeologists (EAA) and the Computer Applications and Quantitative Methods in Archaeology (CAA).

We estimated the gender of the first-named speaker for each presentation using the R programming language and the ‘gender’ package (Blevins and Mullen, 2015; Lincoln, n.d.; Mihaljević et al., 2019). We inferred the gender of personal names by looking each name up in the US Social Security Administration (SSA) baby name data, and calculating the overall probability that a given name was male or female (Mihaljević et al., 2019). If the proportion of people in the SSA data with a certain given name are recorded as female is 0.5 or higher, we recorded the gender of the presenter with this name as female. For example, in the SSA dataset the the name “Lynne” returns 0.006 as proportion of individuals with this name who are recorded as male, and 0.994 as the proportion female, thus we inferred that people in our conference data who are called Lynne are women.

This method of inferring gender has the advantage of rapidly determining gender for a large number of names in a transparent and reproducible way, but it also some substantial limitations that are important to be upfront about. We are only able to infer binary male/female genders and assign the first names into these two categories. This has the unfortunate result of excluding or mis-identifying other genders from the results, excluding them from our analysis. We considered it impractical and invasive to write to each first-named presented to request their gender information. A further limitation of our approach is that it sometimes fails to classify non-English names at all, as the SSA data consists mostly of English names. This means that people with non-English names are underrepresented in our results. It is important to note that the inferences of gender presented here are not self-identified by the presenters, but are computed probabilistically. Better quality and more representative data would result if presenters self-identified their gender to conference organisers, but currently these data are not available. We encourage conference organizers to collect gender data directly from participants to improve the representation of minority genders in future studies. Our hope is that this work, despite (or perhaps because of) its many limitations and biases, will stimulate the collection of more reliable, justifiable, and useful data by conference organisers.

We identified the topic of each presentation by generating a structural topic model for all the presentations in each of the three conferences. Topic modeling is a machine learning method that is widely used to automatically find related groups of words that resemble traditional ‘themes’ or ‘topics’ in large collections of documents. Topic models are ‘unsupervised’ methods because they infer rather than assume the content of the topics in a collection of documents, and they have been used across a variety of fields (Chang et al., 2009). This approach uses latent Dirichlet allocation (LDA) to allow every word to be present in every topic, but with different weightings, such that the most heavily weighted 5-10 words of a topic often capture the essence of the topic as a coherent and familiar concept. When generating topic models, we have to first determine the number of topics that the method will identify in our texts. To prepare our data for topic modelling we excluded words that are common in English generally or in archaeology and so have little semantic value, for example, ‘the,’ ‘a,’ ‘el,’ ‘al,’ ‘archaeology,’ etc. A list of these stopwords is included in our research compendium. We also applied a stemming procedure to words in our documents as part of our pre-processing. Stemming reduces similar words to their common root, for example, ‘technological,’ ‘technologies’ and ‘technology’ all share the common stem of ‘technolog.’ Stemming is useful for removing repetition and transforming words to their base form to simplify interpretation of the output.

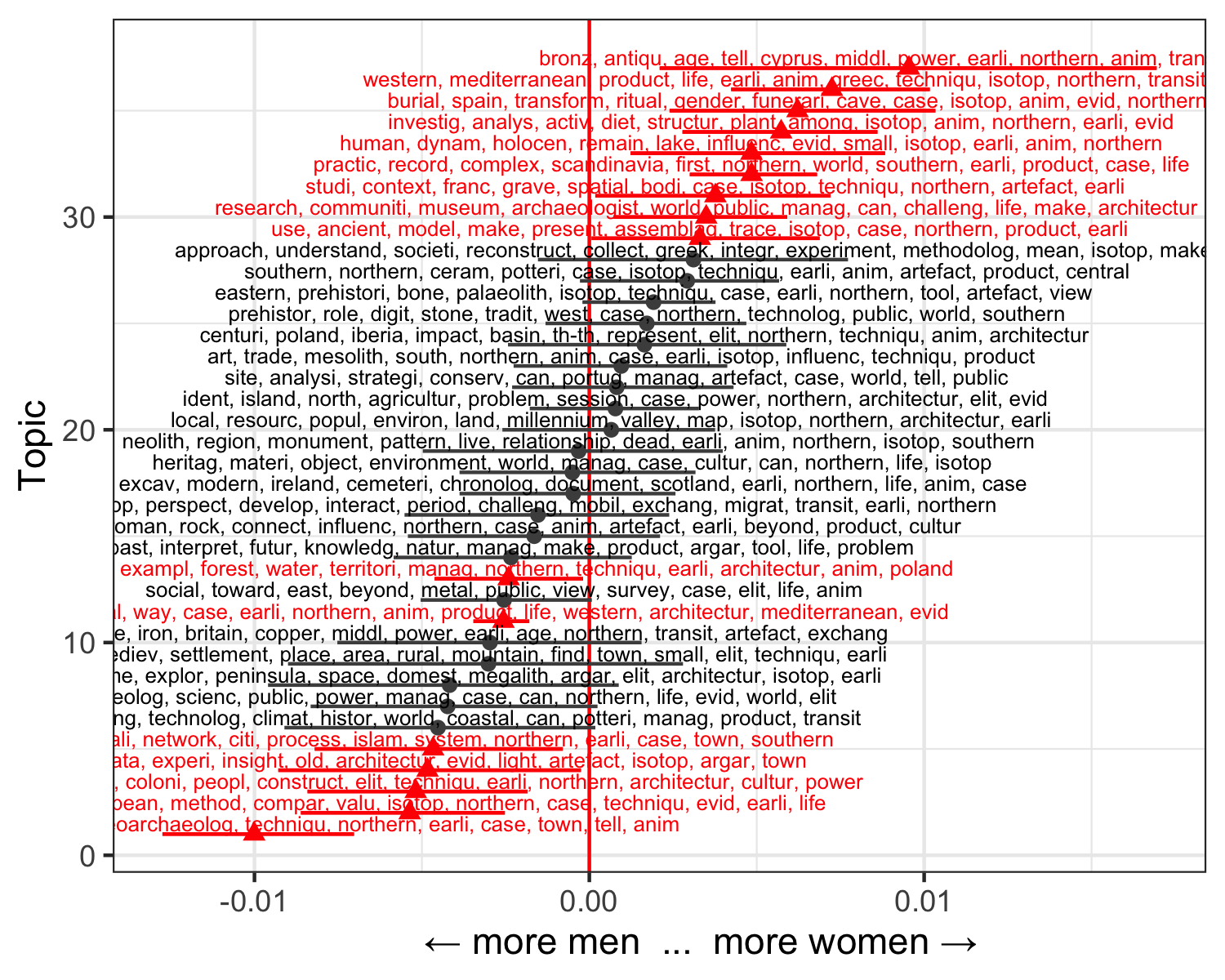
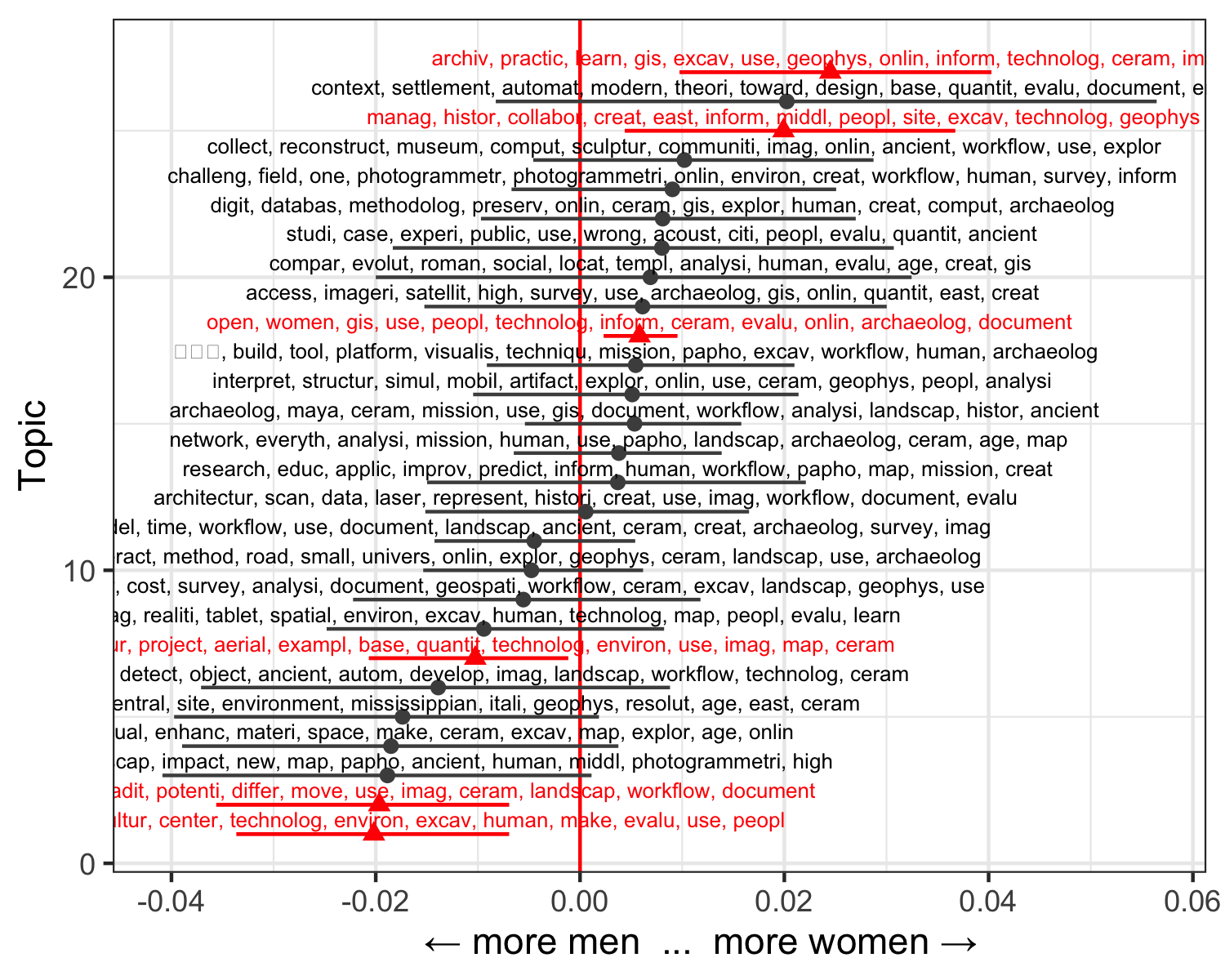
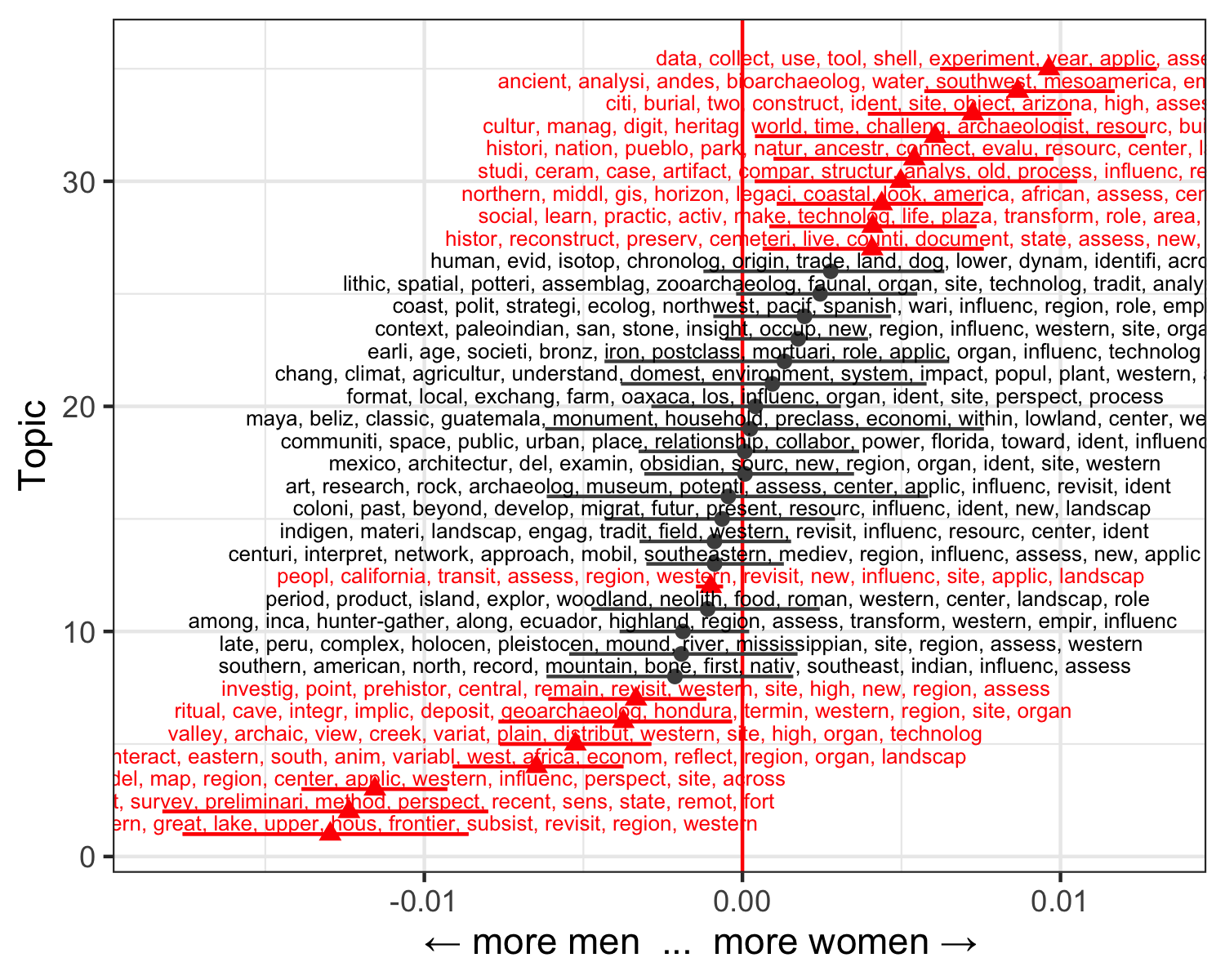
We used the LDA algorithm implemented in the ‘stm’ package which uses the method of Lee and Mimno (2014) to find the optimum number of topics (Mimno and Lee, 2014). This method finds the number of topics by choosing anchor words and using statistical probabilities so that for each assumed topic a specific anchor word will only appear once, after this the algorithm will reconstruct the word co-occurrence patterns for the non-anchor words to create a convex combination of the co-occurrence patterns of those anchor words. Then the algorithm will then choose the farthest point from our subspace until the given number of anchors have been found. It is important to note that because this method is probabilistic, it will not always result in the same number of suggested topics. The topic modeling algorithm then assigns all words in every document into our pre-determined number of topics, and assigns each word a probability based on its per-topic-per-word probability. Similarly, each document (i.e. conference presentation title) is assigned a distribution of topics with different weights. To visualise the topic model output we use the 10 words with the highest weighting within each topic as keywords to represent each topic.

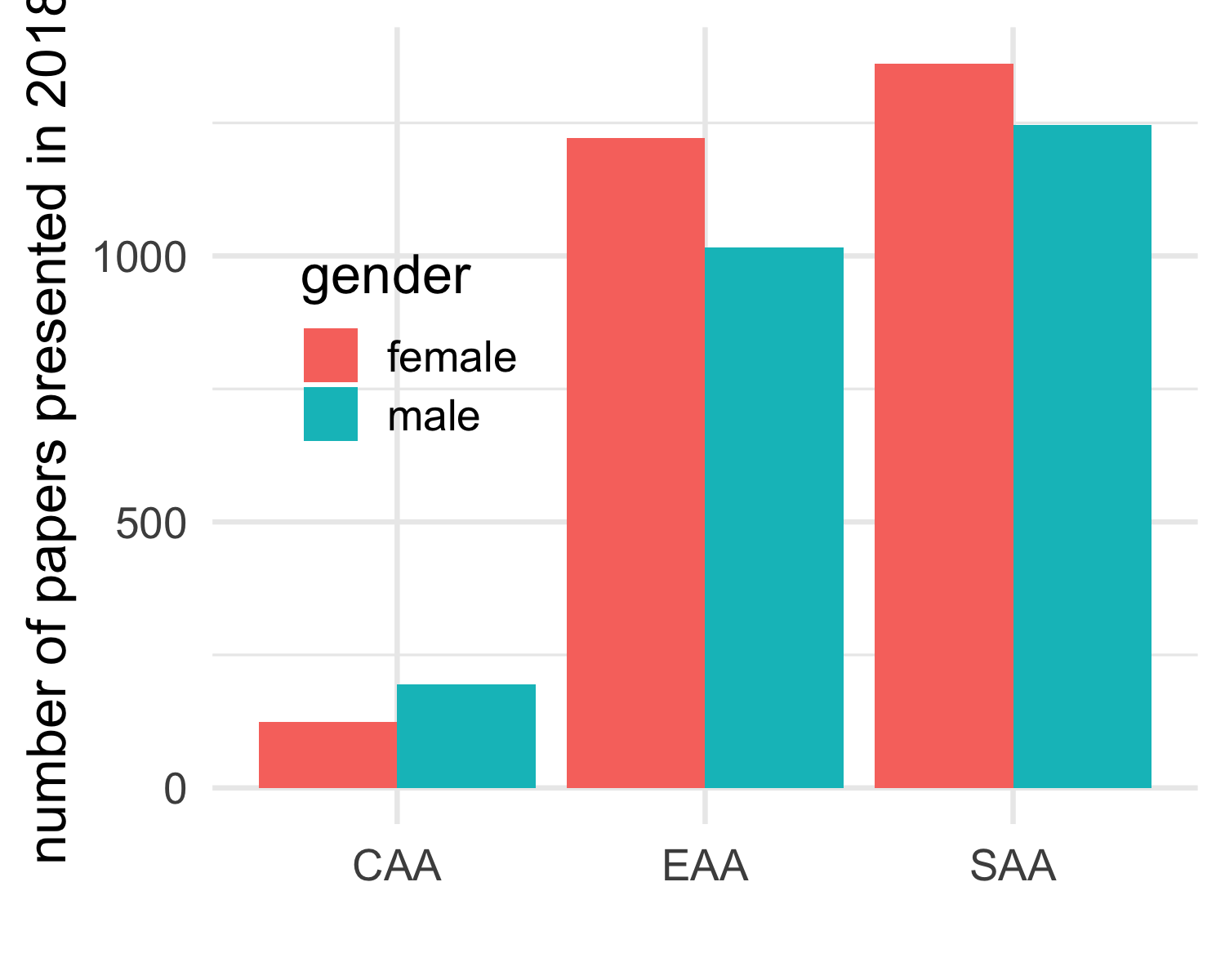
A structural topic model (STM) allows us to include, alongside the typical topic modeling process, other document-level metadata to analyse covariance between topics and metadata (Roberts et al., 2019). Covariates of interest can be included into the prior distributions for document-topic proportions and topic-word distributions using a standard regression model (Roberts et al., 2014). This means that we can examine the relationship between the topics and document-level variables of interest. In our case, we computed the relationship between the inferred the gender of the first-named presenter for each presentation, and the distribution of topics in that person’s presentation. After we observed the topics for each presentation, we then generated a regression where the topic is the outcome variable, and gender is the explanatory variable. This regression gives us insights into whether there are non-random relationships between the inferred gender of an archaeologist and the topics of their presentation. Our data visualisations represent the estimated marginal effect (the x-axis values) of gender on each topic (distributed on the y-axis). Our visualisations show point estimates and 95% confidence intervals for each topic, and we interpret a statistically significant gender effect on the distribution of a topic when the 95% confidence interval does not includ also (also coloured red in our figures).

# Reproducibility and open source materials

The entire R code (R Core Team, 2019) used for all the analysis and visualizations contained in this paper is included in the Supplementary Online Materials at xxx to enable re-use of materials and improve reproducibility and transparency (Marwick, 2017). Also in this version-controlled compendium (Marwick et al., 2018) are the raw data for all the visualizations. The raw data for our analysis are equivalent to the publicly available data available in the conference programs, but are organised here in a tabular structure convenient for computational analysis. All of the figures, tables, and statistical test results presented here can be independently reproduced with the code and data in this repository. The code is released under the MIT license, the data as CC-0, and figures as CC-BY, to enable maximum re-use.

# 5 Results





Overall we see similar women-to-men ratios for the SAA (1.1) and EAA (1.2), but much lower for the CAA (0.6). Even before we look into the gender preferences for specific topics within each conference, we already have a hint that computational topics may be less preferred by women than by men.

In the SAA data we found a total of 2,930 presentations. Of these we could identify the first-named authors of 2608 (89%) presentations as either men (n=1246) or women (n=1362). In the SAA presentations we identified the optimum number of topics as 35, with 17 of these showing non-random co-variance with the gender of the first-named presenter. Eight of these topics were associated with men, and nine topics associated with women. One of the main difference that we can see between the topics of the genders are the locations that the presenters are interested in. Topics associated more with women include bioarchaeology, cemeteries, burials, shells, and ceramics. Topics associated more with men include survey and landscape archaeology, geoarchaeology, rituals, and regional studies. Women are more likely to work on locations such as Mesoamerica, Arizona and national parks, while men are more likely to present on topics about the Great Lakes, and Honduras.

For the EAA data we have 2,928 presentations, and 2237 (76%) where the first author could be classified as either a man (n=1016) or woman (n=1221). For EAA we generated a total of 37 topics, with 16 of these showing non-random co-variance with the gender of the first-named presenter. Seven of these topics were associated with men, and nine topics associated with women. Although topics significantly associated with men and women both include the word “Mediterranean,” women seem to be focusing more on the western Mediterranean while men seems to be focusing on the northern Mediterranean. Topics associated more with women include burials, graves, museums, animals, diet, and ritual. Topics associated more with men include geoarchaeology, architecture, and towns.

For the CAA meeting we have 358 presentations, and 318 (89%) first-named authors could be classified as either men (n=194) or women (n=124). For CAA we generated a total of 27 topics, with 6 of these showing non-random co-variance with the gender of the first-named presenter. Three of these topics were associated with men, and three topics associated with women. Topics associated more with women include archives, GIS, geophysics, collaboration, and teaching. Topics associated more with men include environmental and landscape archaeology.

# 6 Discussion

Our results show significant correlations between the gender of the first-named presenter and the topics in their conference presentation in all three conferences. Although each of the three meetings have distinctive sets of topics, we can identify some common themes in the topics that correlate with gender. We found that topics strongly associated with women at all three conferences relate to managing cultural heritage, GIS, and isotope analyses. Pair-wise shared topics between conferences also reveal the norms of each community. These contrasts and similarities reveal some of the choices that presenters make when deciding where to share their work. The SAA and EAA are defined mostly by the geographic region of their community, the Americas and Europe. They have more participants, and our model identified a higher number of topics in these two, compared to CAA. CAA, with its focus on computer applications and quantitative methods, has a much smaller community, and a smaller number of topics. So we might expect less in common between CAA and the two bigger conferences. At both the SAA and EAA we see that topics about burials, cemeteries, bodies, and graves are strongly associated with women. For the SAA and CAA the shared women-associated topics include learning and practice. For the EAA & CAA the common topics associated with women presenters are self-referential: women and gender. The absence of bioarchaeology and topics about human remains at CAA suggest that either archaeologists working on those topics do not recognise this conference as a meaningful place to present that work, and that there are some unrealised opportunities to apply computational and quantitative methods in bioarchaeological research.

Topics that are strongly associated with men at all three conferences include geoarchaeology and geophysics. Topics associated with men at the SAA and CAA include built-location-based research, indicated by keywords such as house/town/site/fort. At both SAA and CAA we see landscape as a shared topic that is strongly associated with men. For the EAA and CAA there is little overlap in topics strongly associated with men. The geophysics topic is notable here because it is also in the CAA topic that is most strongly associated with women. It is strongly associated with men at the SAA and EAA, but also strongly associated with women at the CAA. This indicates that a topic is not immutably bound to either men or women, but that topics can shift in prominence among genders, depending on the context. This is important for understanding the relationship between genders, topics, and communities. These relationships are flexible and contingent, such that a topic-gender association is specific to a particular community (e.g. conference), and argues against topic-gender generalisations that attempt to transcend communities of practice.

Related work on gender differences in research topics has noted major differences in the proportions of men and women across many academic-related interests. One early and widely discussed theory, especially in psychology, to explain this is the theory of people-thing interest dimensions which proposes that men have stronger interest in things and their mechanisms, while women have a stronger interest in people and their feelings (Miner, 1922; Su et al., 2009). Stoet and Geary (2022) used this theory in their investigation of gender differences in 473,260 adolescents’ aspirations to work in things-oriented (e.g., mechanic), people-oriented (e.g., nurse), and STEM (e.g., mathematician) careers across 80 countries and economic regions using data from the 2018 Programme for International Student Assessment (PISA). They found that boys generally aspired to a things-oriented or STEM occupation and girls to a people-oriented occupation. Some of our results are consistent with this people-thing model, for example, ‘people’ topics such as burials, cemeteries, bodies, graves, collaboration, and teaching are associated more with women than men.

However, recent work by Thelwall et al. (2019) shows that gender differences in choice of research topics cannot be fully explained by people-thing theory from psychology. Thewall et al. looked at 508,283 journal articles, classified the articles into research areas, and determined the authors’ genders by matching names with the 1990 US census data. Instead of a people-thing contrast, they find that women more likely to use exploratory and qualitative methods rather than quantitative methods, and men show more interest in male in abstraction, and power/control fields. In our data, we can similarly see in an interest from men in quantitative methods. However, our results do not so clearly divide the interests of the two genders we have data on, for example, with women are more prominent in GIS, and isotope analyses, which are highly quantitative areas.

Ostapenko et al. (2018) identified common topics in the personal statements of aspiring surgeons that were specific to men and women authors. Women tended to discuss surgery as working as a team, while men focused on their specific individual clinical experiences. Ostapenko et al. (2018) propose that the differences between male and female statements may come from actual motivating factors for career goals and aspirations, or they may reflect differences in beliefs about what makes a successful personal statement. They could not evaluate which explanation was most important, but a key observation is that authors of the personal statements may not deliberately choose the themes for their statements. Instead, they may be using themes that they have received positive feedback on on the past, that has perhaps unconsciously biased them towards certain themes in their writing. Similarly archaeologists might choose topics for their research based on a pattern of positive or negative feedback on topic choices over time, and so their choices are not fully deliberate.

Theories such as people-thing and Thewall et al’s exploratory/abstraction assume that researchers freely make choices about their research preferences, and that these choices are influenced by inborn cognitive differences. However, these approaches do not fully explain gender differences in topic choices. A meta-analysis of gender and science research by the European Commission (Caprile et al., 2012) found that structural and life-course factors also profoundly shape the distribution of genders in research fields. Socialisation factors, such as media representation of scientists and family role models strongly shape career choices. Life-course factors include the ‘rush hour’ which is the time when family and academic demands collide and pivotal decisions are made about whether or not to have children and how much to invest or sacrifice for an academic career. Historically this is a time that leads to women making different choices to their male peers, but this can also affect caregivers of any gender. For example, caregivers may be less mobile to conduct field research or relocate for career advancement. This may explain the prominence of women in GIS, and isotope analyses, which may be pursued without requiring travel for fieldwork. These structural and life-course factors may add up to subtle, but pervasive exclusionary practices the skew gender representation in research fields that are independent of individual choices and preferences.

A key limitation of this study is our concept of gender itself, and how we measure it. Like many social science studies, we have measured gender assuming it has two binary categories. However, we recognise that many cultures have long included more than two genders (Graham, 2004; Wilson, 1996), and there is a growing awareness of this in Western cultures also. A better measure of gender would represent it as a multifaceted spectrum (Tobin et al., 2010). The problem with our binary measure is that it does not reflect our current understanding of gender, forces people in misclassified categories, and is hostile to public acceptance and advocacy for transgender and nonbinary individuals. Our instrument for collecting gender data only returns two categories, so this has limited potential for overcoming this limitation. To overcome this limitation, we recommend that conference organisers collect gender information directly from presenters using inclusive gender measures. For example, by providing nonbinary options for presenters on registration forms, and by asking about gender as an open‐ended question for participants to self-identify. We recommend that future work on gender in archaeology avoid ‘othering’ language when describing results. For example, reporting a sample as ‘150 participants (48% women; 49% men; 3% other)’ violates ethical standards because such wording implies that binary gender is normal or appropriate, whereas trans and nonbinary gender is not (it is ‘other’). Our hope is that our study might be the last one done by archaeologists to discuss gender as a binary.

# 7 Conclusion

We find consistent associations of topics and genders across the three conferences. Like much previous work (Lippa, 2005), the associations we observed are not easily explained by conventional models such as people/thing or exploratory/abstraction models. We speculate that the patterns in our data may result from a combination subtle, implicit biases that shape the decisions made by early career researchers and their advisers and mentors, as a well as large scale structural constraints that make certain topics more accessible for one gender than others.

Our results are important because they include scholars at the beginning of their career, such as students and post-doctoral researchers that have yet to publish in a peer reviewed journal, and thus not represented or underrepresented in studies of gender and publication patterns. As such, our findings have implications for how archaeologists are trained and mentored at the early stages of their career. First, instructors and mentors should be alert to unintentionally recommending students into classes, research projects and laboratory or field experiences that might appear to suit their gender, for example, ‘people’ topics for women students, rather than presenting students with a variety of topics and encouraging students to choose based on their interests. Second, senior archaeologists should be intentional about removing structural limitations to participation in certain topics by gender. For example, support for childcare expenses should be available for career-relevant travel, such as field work. This may help to equalize professional mobility for women researchers who may have limited capacity to travel with young children. Third, departments that train archaeologists should ensure that hiring practices support a high diversity of topics, and equal representation of genders to minimize historical effects of low diversity that will canalize gender-topic associations, making it harder for students to freely choose research topics.

Brown (2018) found the low rate of women as professors, and other senior leadership positions in archaeology results in a confounding effect on female students’ ability to find suitable models and mentors. Our work indicates that the negative effects of a low rate of women professors is not limited to female students, because without women professors, students of any gender may be unable to pursue certain research topics that currently tend to be pursued by women. Similarly, supporting womens’ participation in fieldwork is likely to have a positive effect for junior researchers of all genders, who can benefit from increased sharing of expertise on topics currently concentrated among women researchers. It is our hope that studies such as ours will stimulate a more active consideration of gender-topic associations that will lead to a more equitable future for archaeology.

# 8 Acknowledgements

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### 9.0.1 Colophon

This report was generated on 2022-02-07 14:36:57 using the following computational environment and dependencies:

#> ─ Session info ───────────────────────────────────────────────────────────────  
#> setting value  
#> version R version 4.1.2 (2021-11-01)  
#> os macOS Catalina 10.15.7  
#> system x86\_64, darwin17.0  
#> ui X11  
#> language (EN)  
#> collate en\_US.UTF-8  
#> ctype en\_US.UTF-8  
#> tz America/Los\_Angeles  
#> date 2022-02-07  
#> pandoc 2.14.0.3 @ /Applications/RStudio.app/Contents/MacOS/pandoc/ (via rmarkdown)  
#>   
#> ─ Packages ───────────────────────────────────────────────────────────────────  
#> package \* version date (UTC) lib source  
#> assertthat 0.2.1 2019-03-21 [1] CRAN (R 4.1.0)  
#> backports 1.4.1 2021-12-13 [1] CRAN (R 4.1.0)  
#> bookdown 0.24 2021-09-02 [1] CRAN (R 4.1.0)  
#> brio 1.1.3 2021-11-30 [1] CRAN (R 4.1.0)  
#> broom 0.7.11 2022-01-03 [1] CRAN (R 4.1.2)  
#> cachem 1.0.6 2021-08-19 [1] CRAN (R 4.1.0)  
#> callr 3.7.0 2021-04-20 [1] CRAN (R 4.1.0)  
#> cellranger 1.1.0 2016-07-27 [1] CRAN (R 4.1.0)  
#> cli 3.1.1 2022-01-20 [1] CRAN (R 4.1.2)  
#> colorspace 2.0-2 2021-06-24 [1] CRAN (R 4.1.0)  
#> crayon 1.4.2 2021-10-29 [1] CRAN (R 4.1.0)  
#> data.table 1.14.2 2021-09-27 [1] CRAN (R 4.1.0)  
#> DBI 1.1.2 2021-12-20 [1] CRAN (R 4.1.0)  
#> dbplyr 2.1.1 2021-04-06 [1] CRAN (R 4.1.0)  
#> desc 1.4.0 2021-09-28 [1] CRAN (R 4.1.0)  
#> devtools 2.4.3 2021-11-30 [1] CRAN (R 4.1.0)  
#> digest 0.6.29 2021-12-01 [1] CRAN (R 4.1.0)  
#> dplyr \* 1.0.7 2021-06-18 [1] CRAN (R 4.1.0)  
#> ellipsis 0.3.2 2021-04-29 [1] CRAN (R 4.1.0)  
#> evaluate 0.14 2019-05-28 [1] CRAN (R 4.1.0)  
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#> farver 2.1.0 2021-02-28 [1] CRAN (R 4.1.0)  
#> fastmap 1.1.0 2021-01-25 [1] CRAN (R 4.1.0)  
#> forcats \* 0.5.1 2021-01-27 [1] CRAN (R 4.1.0)  
#> fs 1.5.2 2021-12-08 [1] CRAN (R 4.1.0)  
#> gender \* 0.6.0 2021-10-13 [1] CRAN (R 4.1.0)  
#> genderdata 0.6.0 2022-01-31 [1] Github (lmullen/genderdata@df16017)  
#> generics 0.1.1 2021-10-25 [1] CRAN (R 4.1.0)  
#> ggplot2 \* 3.3.5 2021-06-25 [1] CRAN (R 4.1.0)  
#> glue 1.6.1 2022-01-22 [1] CRAN (R 4.1.2)  
#> gtable 0.3.0 2019-03-25 [1] CRAN (R 4.1.0)  
#> haven 2.4.3 2021-08-04 [1] CRAN (R 4.1.0)  
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#> highr 0.9 2021-04-16 [1] CRAN (R 4.1.0)  
#> hms 1.1.1 2021-09-26 [1] CRAN (R 4.1.0)  
#> htmltools 0.5.2 2021-08-25 [1] CRAN (R 4.1.0)  
#> httr 1.4.2 2020-07-20 [1] CRAN (R 4.1.0)  
#> jsonlite 1.7.3 2022-01-17 [1] CRAN (R 4.1.2)  
#> knitr 1.37 2021-12-16 [1] CRAN (R 4.1.0)  
#> labeling 0.4.2 2020-10-20 [1] CRAN (R 4.1.0)  
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#> rmarkdown 2.11 2021-09-14 [1] CRAN (R 4.1.2)  
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#> rvest 1.0.2 2021-10-16 [1] CRAN (R 4.1.0)  
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#> tidyverse \* 1.3.1 2021-04-15 [1] CRAN (R 4.1.0)  
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#> utf8 1.2.2 2021-07-24 [1] CRAN (R 4.1.0)  
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#> yaml 2.2.2 2022-01-25 [1] CRAN (R 4.1.2)  
#>   
#> [1] /Library/Frameworks/R.framework/Versions/4.1/Resources/library  
#>   
#> ──────────────────────────────────────────────────────────────────────────────

The current Git commit details are: u

#> Local: master /Users/bmarwick/Desktop/archyconfgender  
#> Remote: master @ origin (https://github.com/yichun33/archyconfgender)  
#> Head: [b7ec24b] 2021-03-15: added basic plot of data