Fields of Study of Women in Computer Science

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Introduction

It is common knowledge that there is gender disparity in the field of computer science. While women played an impactful role in the early days of computing, there has been a steady decline in female representation in computer science since the 1970’s.

Computer science is a broad area of study with many subfields. Since women and men often choose different career paths, do they also choose different areas to study within computer science? How many papers do women publish in the field? How many others do they tend to collaborate with and what is their average position in the author list? This project analyses the fields of study and publishing trends of women in computer science.

Materials and Methods

Data Collection and Management

The source data about the authors was collected from dblp.org. The dblp is a database that provides bibliographic information from major computer science journals and conferences. The data was obtained by both downloading the entire database as a raw XML and by using their API.

The data collected from the XML using the python program dblp_parser.py. The dblp_parser.py program parsed the dblp XML file incrementally with the etree library and saved it incrementally as a JSON file with the tinyDB library.

The data outputted from the dblp_parser was stored as a JSON file named db.json with the following fields:

Name	Datatype	Description
name	string	A unique author name from the dblp
titles	string	A string of publication titles by the author, delimited by a semi-colon

Because the xml file was so large (5.3 million publications from 2.6 million authors), only a sample from the dblp was collected.

The db.json file was then processed by the dblp_genderize.py program. The program iterated through each entry and then, using Genderize.io's API, predicted the author's gender using their first name. Because there was a limit of 1000 queries a day from the Genderize.io and just first names were used, any name queried was saved into the JSON file names.json with the following fields:

Name	Datatype	Description
name	String	The first name supplied for gender prediction
gender	String	The predicted gender
probability	Number	Certainty of predicted gender
count	Number	Rows examined by Genderize.io to calculate the response

In subsequent iterations of the program, if the first name had already been processed, the program would draw from the local file, rather than use the API therefor saving a query from the daily limit.

The program then preprocessed the string of titles to prepare for classification. Because many of the titles are not in English, some must be translated before the classification process. The program determines if the titles are in English using the langdetect library and if they are not detected as English, there is an attempt to translate them using the DeepL language translation API. The titles are then set to lowercase, all non-alphabetic characters are removed, stop words are removed and the remaining words are stemmed. The stopwords and stemming libraries are imported from the natural language toolkit (nltk).

The data is stored in json files with the following fields:

Name	Datatype	Description
author	String	The first name supplied for gender prediction
titles	String	A string of publication titles by the author, delimited by a semi-colon
cleanedtitles	String	A string the cleaned titles
gender	String	The predicted gender
probability	number	Certainty of predicted gender
count	number	Rows examined by Genderize.io to calculate the response

translation	string	A field that only appears if the titles were translated before cleaning

The all the data processed was saved into the authorData.json file. If the author was predicted to be female with a count of over 20 and a probability greater than or equal to 90% then it was also saved into the authorFemaleData.json file.

This process, unfortunately, further reduced the size of the sample as the 1000 daily limit for Genderize.io meant only allowed me to predict the genders of 7218 first names.

The data collected to this point only contained the name, titles, and gender of the author. To gather further information about each author, the extra_info.py program used the dblp's API to gather extra information about each author from the authorData.json file. The extra data collected was stored in the authorExtraData.json file with the following data fields:

Name	Datatype	Description
name	String	A unique author name from the dblp
Pid	String	A unique author ID from the dblp
Gender	String	The predicted gender
gender probability	number	Certainty of predicted gender
gender count	number	Rows examined by Genderize.io to calculate the response
total publications	number	Total publications recorded by the dblp
Publications	List	List of publications
publications:title	String	Title of publication
Publications:translation	String	Optional field: Translation of the title
publications:cleaned titles	String	Cleaned title
publications:title:authors:	List	List of authors of the publication
publications:title:authors:name	String	Author name of the publication
publications:title:authors:pid	String	A unique author ID
publications:position	number	Positional index of the queried author in the author's list
publications:venue	String	Optional field: Location of the publication's presentation
publications:pages	String	Optional field: Page number of the publication in a journal
publications:volume	String	Optional field: Volume of the journal
publications:publisher	String	Optional field: Publisher's name
publications:year	String	Optional field: Year of publication
publications:type	String	Optional field: Type of publication
publications:key	String	The dblp's unique publication key
publications:doi	String	Optional field: Digital Object Identifier
publications:ee	String	Optional field: Electronic Engineering URL
publications:url	String	Optional field: URL of the publication
average pages	number	Optional field: Average number of publication pages of the author
average position	number	Average author position in research publications
average authors	number	Average number of authors per publication
most recent publication	number	Optional field: Year of most recent publication
title(string)	String	Publication titles by the author, delimited by a semi-colon from authorData (may not be complete)

cleaned titles	String	The cleaned titles from authorData (may not be complete)
all titles	String	A string of all cleaned titles

Predicting the author's most likely field of publication required a training and validation dataset. To generate this dataset data_preprocessing.py scraped Wikipedia's definitions of computer science fields from the site's outline of computer science. This program used Wikipedia's API to gather the content from each of the subfield pages. The content was chunked into sentences and then cleaned. The cleaning process included setting the text to lowercase, removing URLs, removing non-alphabetic characters, removing stopwords, and stemming the remaining words with NLTK library. The dataset was stored in dataset.csv with the following fields:

Name	Datatype	Description
subfield	String	Title of a subfield of computer science
description	String	Description of subfield
field	String	Title of a field in computer science
url	String	URL of Wikipedia's subfield page
content	String	Cleaned string for classification

Classification

Four different classification models were used to predicts the author's primary field in computer science:

- Naïve Bayes classifier with count vectors
- Naïve Bayes classifier with TF-IDF vectors
- Multinomial logistic regression classifier with count vectors
- Multinomial logistic regression classifier with TF-IDF vectors

The program model_fitting.py was used to create these models using sklean – a machine learning library.

First the Wikipedia dataset was broken into a training set comprised of 75% of the data, and a validation set of 25% of the data. The labels (the computer science fields) were then encoded into integers.

The observations were then transformed into two types of vectors: count vectors and TF-IDF vectors. Both are representations of frequency of tokens in a corpus with count vectors being a straightforward integer representation of frequency of words and TF-IDF vectors penalizing common words and giving importance to more frequent terms.

Using the transformed vectors, the classifier models were trained. First, the Naïve Bayes classifier was trained. This classifier is based off the Bayes theorem. The multinomial Naïve Bayes classifier was used because the label is categorical and there are more than two possible labels. The other model type that was trained is the multinomial logistic regression classifier. This type of classifier is used for categorical labels and is an extension of logistic regression (which is a binary classifier) and it is called multinomial it is classifying more that two labels.

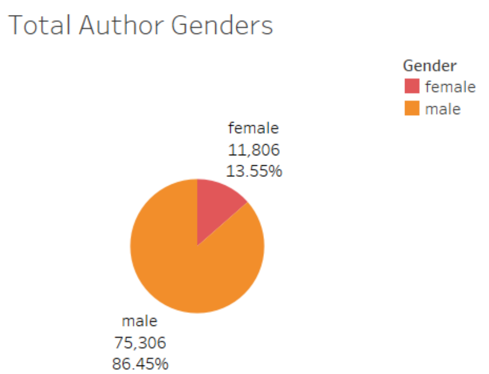
The classifiers models had the following accuracy (based off the validation set created with the Wikipedia pages):

Model	Model Accuracy
Naive Bayes classifier with count vectors:	0.704537071
Naive Bayes classifier with TF-IDF Vectors:	0.611213574
Logistic regression classifier with count vectors:	0.699004058
Logistic regression classifier with TF-IDF vectors:	0.706381409

Finally, the records were classified with models with the program classify.py. The results were outputted to results.csv and imported into Tableau for data visualization. The records were also processed with stats.py to gather some simple stats about the data.

Results

Gender	% of Total	Number
female	13.55%	11,806
male	86.45%	75,306



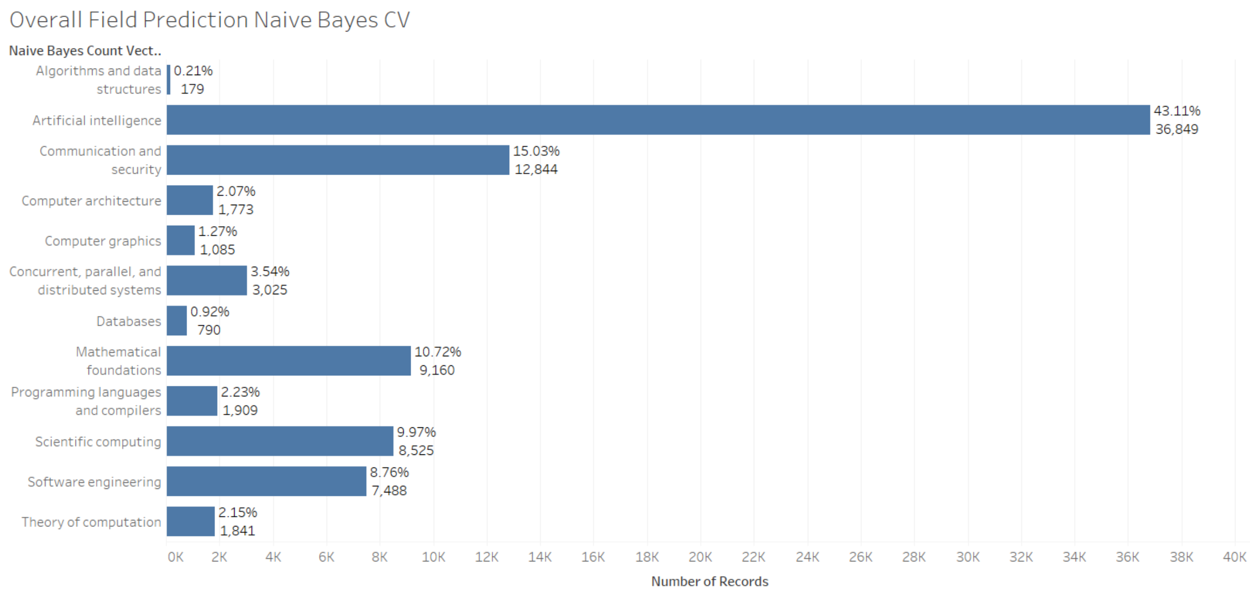
After the data collection and cleaning process there were 87,112 records left to be analysed. 13.5% of the records were classified as female and 86.5% were classified as male, each with a accuracy of 90% and higher.

The classifier process produced the following results:

Naive Bayes Count Vector Field Prediction

Naive Bayes Count Vector Field Prediction	% of Total Number of Records	Number of Records
Theory of computation	2.15%	1,841
Software engineering	8.76%	7,488
Scientific computing	9.97%	8,525
Programming languages and compilers	2.23%	1,909
Mathematical foundations	10.72%	9,160
Databases	0.92%	790
Concurrent, parallel, and distributed systems	3.54%	3,025
Computer graphics	1.27%	1,085
Computer architecture	2.07%	1,773
Communication and security	15.03%	12,844

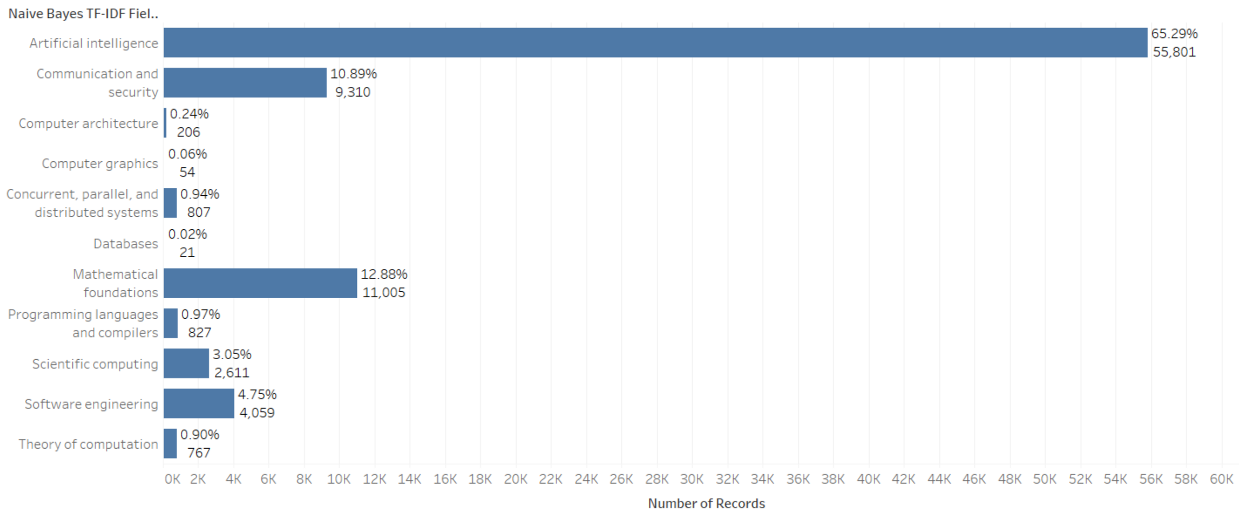
Artificial intelligence	43.11%	36,849
Algorithms and data structures	0.21%	179



Naive Bayes TF-IDF Field Prediction

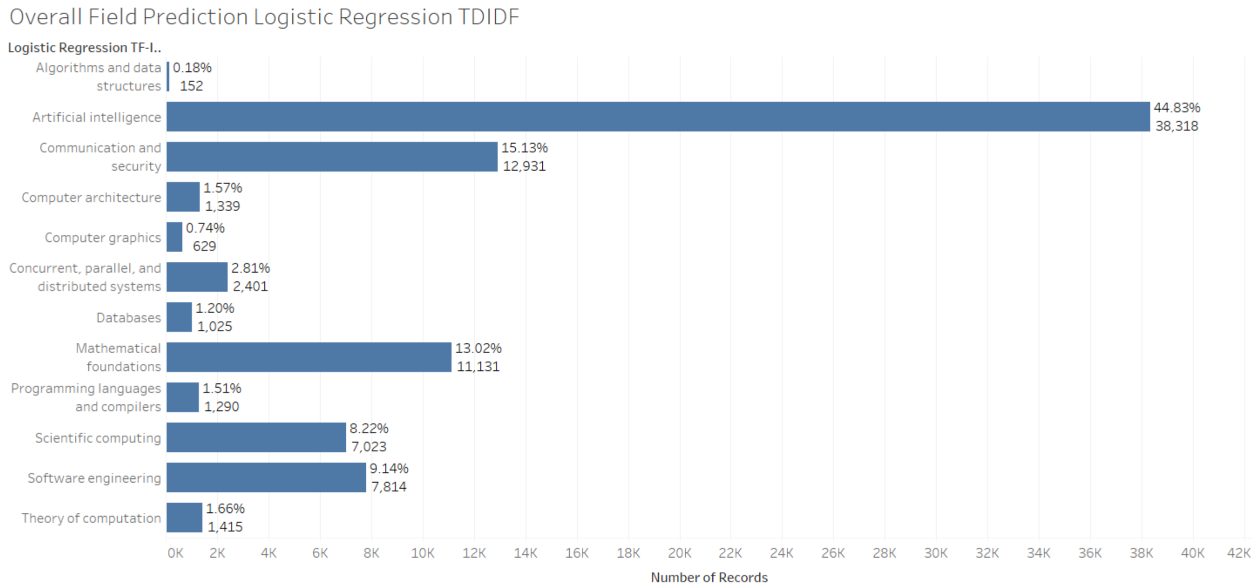
Naive Bayes TF-IDF Field Prediction	% of Total Number of Records	Number of Records
Theory of computation	0.90%	767
Software engineering	4.75%	4,059
Scientific computing	3.05%	2,611
Programming languages and compilers	0.97%	827
Mathematical foundations	12.88%	11,005
Databases	0.02%	21
Concurrent, parallel, and distributed systems	0.94%	807
Computer graphics	0.06%	54
Computer architecture	0.24%	206
Communication and security	10.89%	9,310
Artificial intelligence	65.29%	55,801

Overall Field Prediction Naive Bayes TDIDF



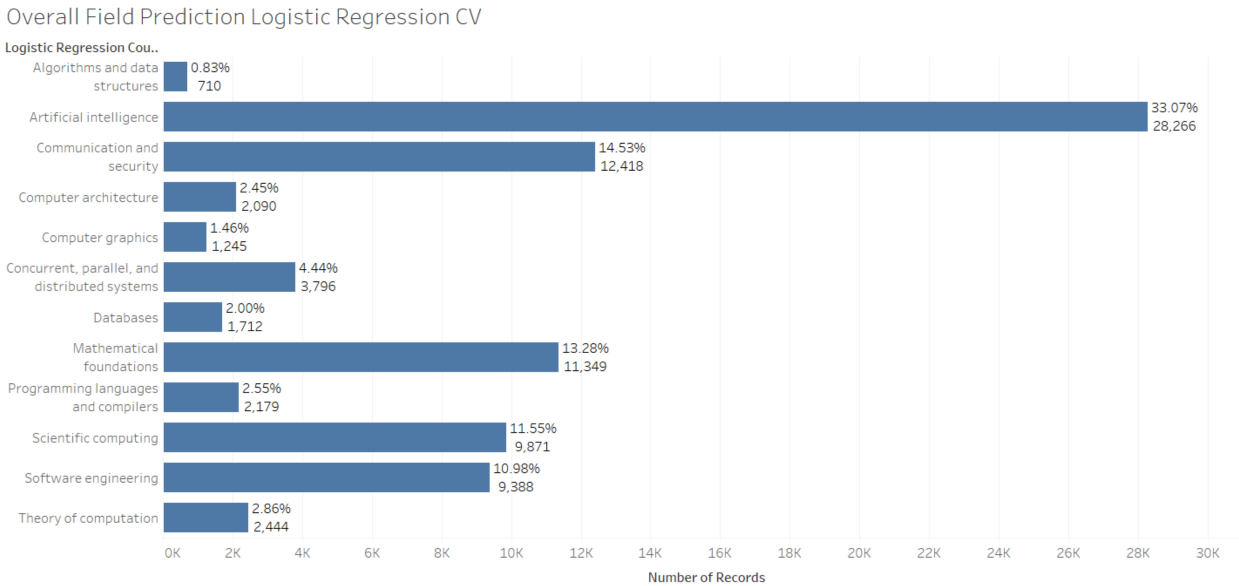
Logistic Regression TF-IDF Field Prediction

Logistic Regression TF-IDF Field Prediction	% of Total Number of Records	Number of Records
Theory of computation	1.66%	1,415
Software engineering	9.14%	7,814
Scientific computing	8.22%	7,023
Programming languages and compilers	1.51%	1,290
Mathematical foundations	13.02%	11,131
Databases	1.20%	1,025
Concurrent, parallel, and distributed systems	2.81%	2,401
Computer graphics	0.74%	629
Computer architecture	1.57%	1,339
Communication and security	15.13%	12,931
Artificial intelligence	44.83%	38,318
Algorithms and data structures	0.18%	152



Logistic Regression Count Vector Field Prediction

Logistic Regression Count Vector Field Prediction	% of Total Number of Records	Number of Records
Theory of computation	2.86%	2,444
Software engineering	10.98%	9,388
Scientific computing	11.55%	9,871
Programming languages and compilers	2.55%	2,179
Mathematical foundations	13.28%	11,349
Databases	2.00%	1,712
Concurrent, parallel, and distributed systems	4.44%	3,796
Computer graphics	1.46%	1,245
Computer architecture	2.45%	2,090
Communication and security	14.53%	12,418
Artificial intelligence	33.07%	28,266
Algorithms and data structures	0.83%	710

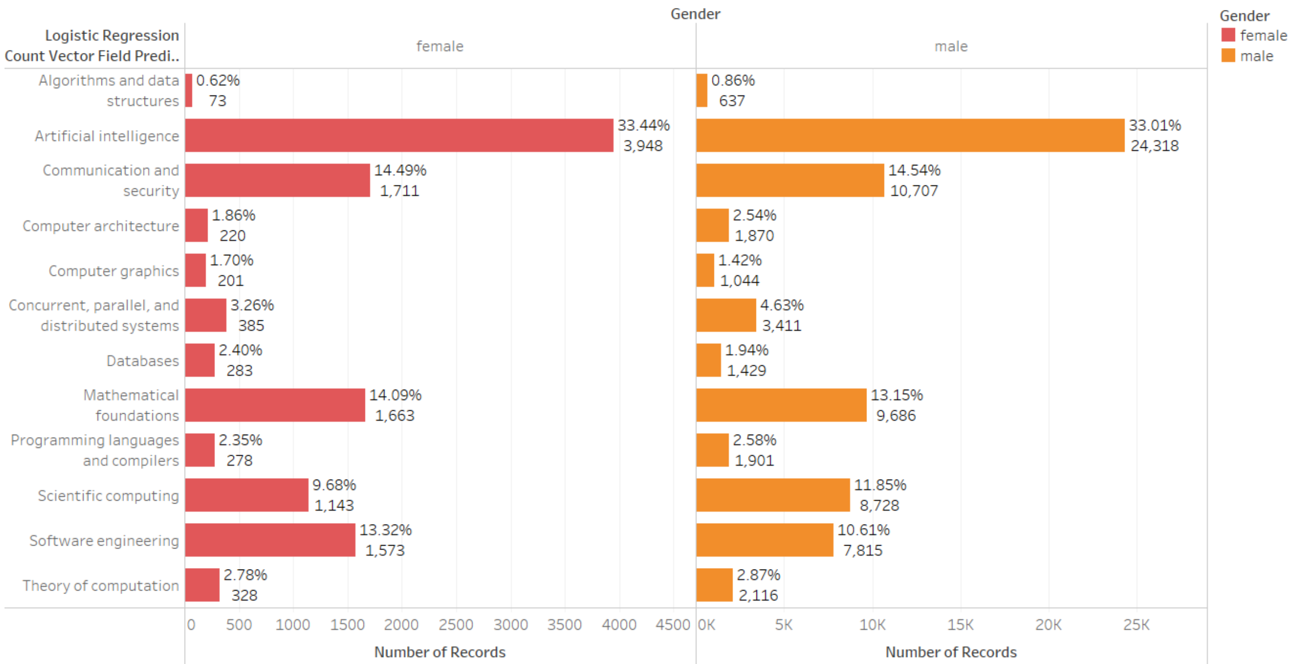


With all four classification models, Artificial Intelligence had the largest classification rate, however, the records seemed to be categorized more evenly with the multinomial logistic regression model. I chose this model to predict the fields of the authors between the genders:

Gender	Logistic Regression Count Vector Field Prediction	% of Total Number of Records	Number of Records
female	Theory of computation	2.78%	328
female	Software engineering	13.32%	1,573
female	Scientific computing	9.68%	1,143
female	Programming languages and compilers	2.35%	278
female	Mathematical foundations	14.09%	1,663
female	Databases	2.40%	283
female	Concurrent, parallel, and distributed systems	3.26%	385
female	Computer graphics	1.70%	201
female	Computer architecture	1.86%	220
female	Communication and security	14.49%	1,711
female	Artificial intelligence	33.44%	3,948
female	Algorithms and data structures	0.62%	73
male	Theory of computation	2.87%	2,116
male	Software engineering	10.61%	7,815
male	Scientific computing	11.85%	8,728
male	Programming languages and compilers	2.58%	1,901
male	Mathematical foundations	13.15%	9,686
male	Databases	1.94%	1,429
male	Concurrent, parallel, and distributed systems	4.63%	3,411
male	Computer graphics	1.42%	1,044
male	Computer architecture	2.54%	1,870

male	Communication and security	14.54%	10,707
male	Artificial intelligence	33.01%	24,318
male	Algorithms and data structures	0.86%	637

Field Prediction by Gender



The results indicate that women and men seem to publish approximately equally across the different fields of computer science although more seem women to choose software engineering, and less women tend to choose scientific computing.

Women’s publication habits

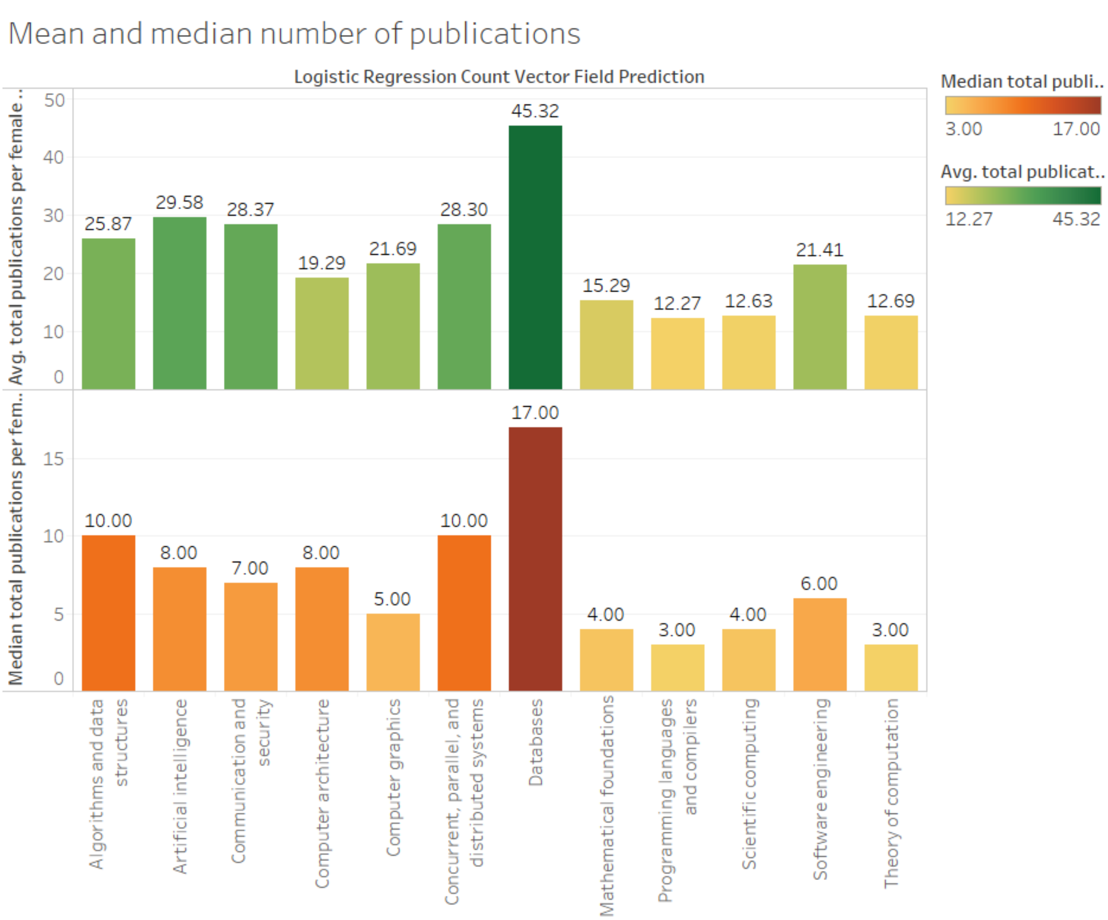
To investigate the women’s publication habits, the means and medians were first calculated across for these four categories:

	Average	Median
Number of publications by female authors	24.76	6.00
Number of pages per publications by female authors	10.86	9.91
Number of authors per publications by female authors	3.93	3.50
Position of female authors on publications	1.36	1.00

Then each category was further analysed to see if there was any deviation across the field of study.

Number of publications

Logistic Regression Count Vector Field Prediction	Avg. total publications per female author	Median total publications per female author
Theory of computation	12.68965517	3
Software engineering	21.41008626	6
Scientific computing	12.63033175	4
Programming languages and compilers	12.26946108	3
Mathematical foundations	15.29438543	4
Databases	45.31569966	17
Concurrent, parallel, and distributed systems	28.29879518	10
Computer graphics	21.69230769	5
Computer architecture	19.29147982	8
Communication and security	28.36998255	7
Artificial intelligence	29.57998037	8
Algorithms and data structures	25.86885246	10

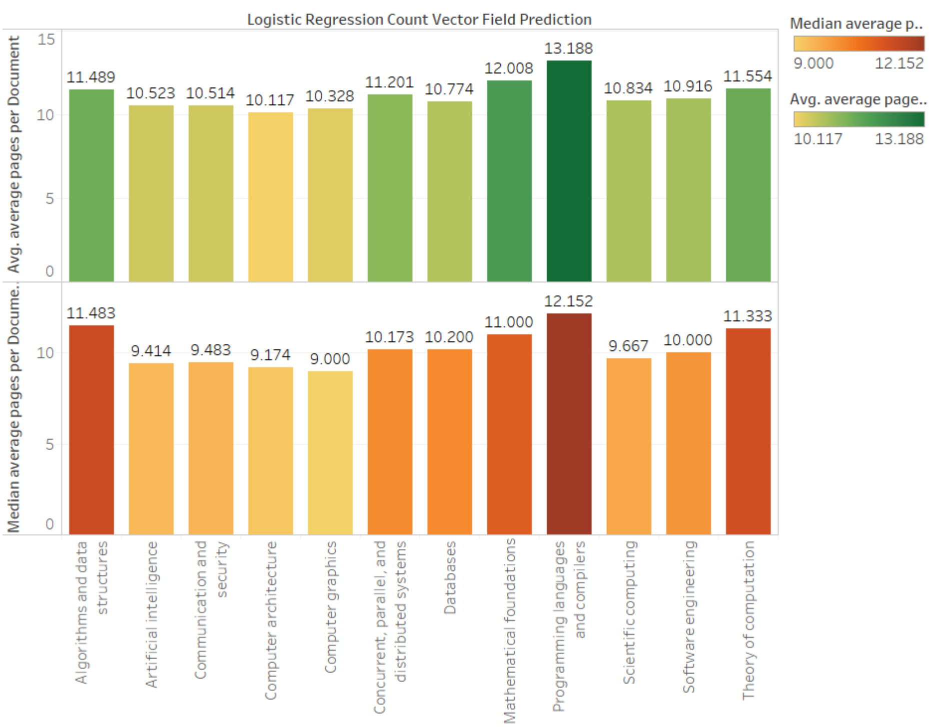


There seemed to be a large difference in the number of publication across fields, where programming languages and theory of computation had the lowest median number of publications with three publications, and the authors with the largest number of publications seemed to be from the database field.

Length of publications

Logistic Regression Count Vector Field Prediction	Avg. average pages per Document	Median average pages per Document
Algorithms and data structures	11.48885457	11.482759
Artificial intelligence	10.52303317	9.4137931
Communication and security	10.51436075	9.4833333
Computer architecture	10.1170135	9.173913
Computer graphics	10.32841904	9
Concurrent, parallel, and distributed systems	11.20140836	10.172619
Databases	10.77352621	10.2
Mathematical foundations	12.00788706	11
Programming languages and compilers	13.1884533	12.152299
Scientific computing	10.83424187	9.6666667
Software engineering	10.91639362	10
Theory of computation	11.55374027	11.333333

Mean and median paper length

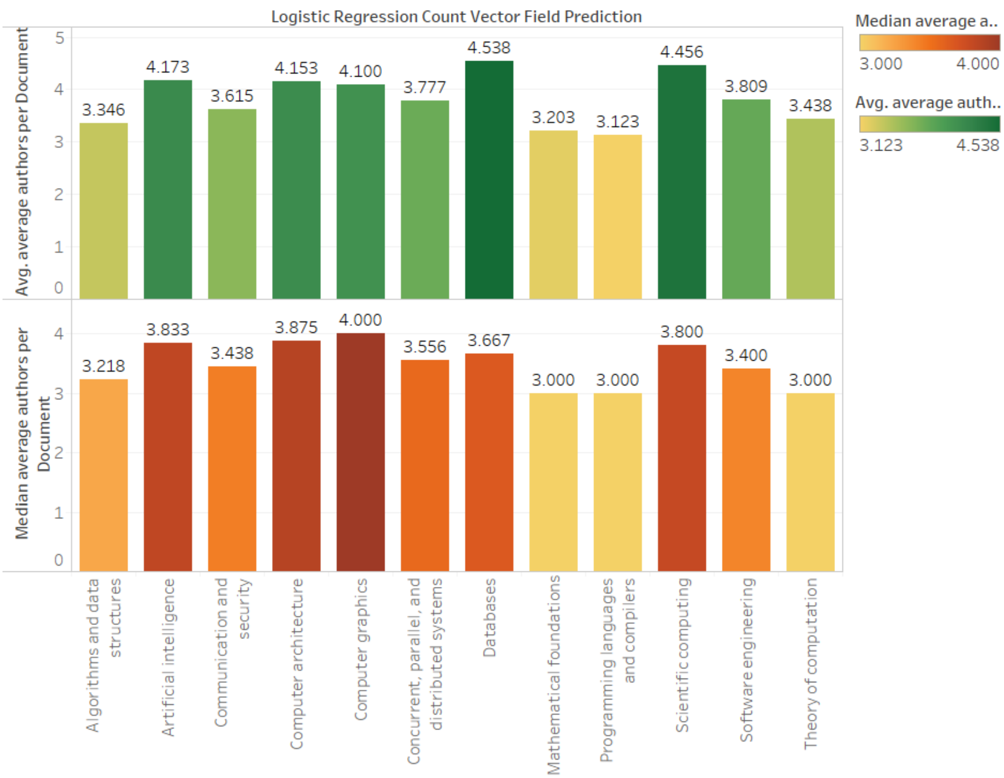


The median range of pages was 9-12.1 pages in length. There did not seem to be a large difference in length of publications across fields, but programming language publications seem to have the most length at median 12.152 pages.

Number of collaborators

Logistic Regression Count Vector Field Prediction	Avg. average authors per Document	Median average authors per Document
Algorithms and data structures	3.346207659	3.218254
Artificial intelligence	4.172904606	3.8333333
Communication and security	3.614809593	3.4375
Computer architecture	4.152699467	3.875
Computer graphics	4.100071363	4
Concurrent, parallel, and distributed systems	3.777231894	3.5555556
Databases	4.538215694	3.6666667
Mathematical foundations	3.202932286	3
Programming languages and compilers	3.123077417	3
Scientific computing	4.455903083	3.8
Software engineering	3.809188473	3.4
Theory of computation	3.43820002	3

Mean and median author collaboration

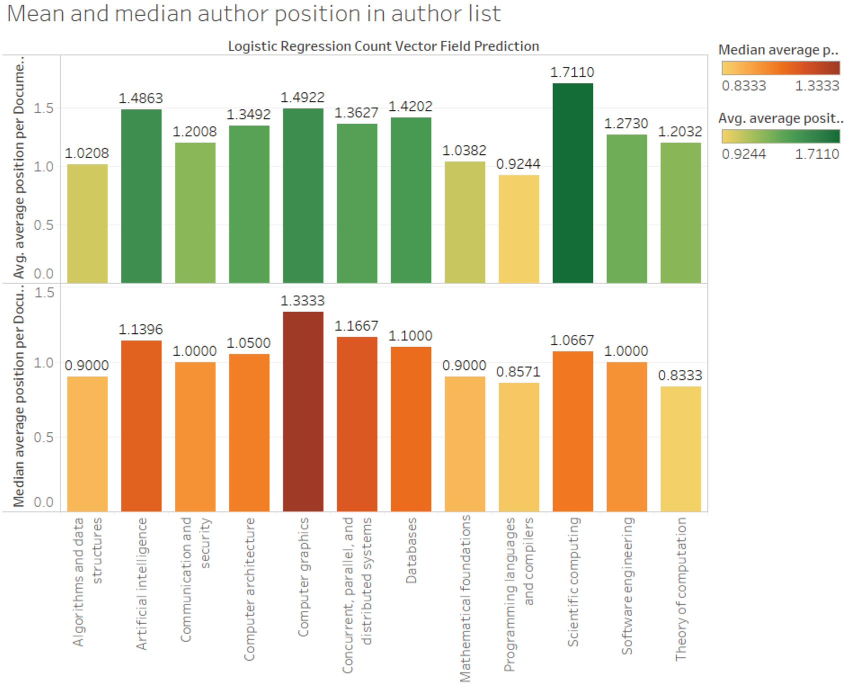


Again, the numbers seemed somewhat consistent across the different predicted fields of study, with a range of 3.1 to 4.538 collaborators for the female authors. There seemed to be an increase in collaborators in the fields of databases and scientific computing with each of them having an average of over 4.5. The field of programming languages and compliers seems to be a field where collaboration happens less or where it happens with less people. The average number of collaborators in that field is 3.123 per publication.

Author's position

Logistic Regression Count Vector Field Prediction	Avg. average position per Document	Median average position per Document
Algorithms and data structures	1.020828327	0.9
Artificial intelligence	1.486277272	1.1396104
Communication and security	1.200830604	1
Computer architecture	1.349218619	1.05
Computer graphics	1.492225112	1.3333333
Concurrent, parallel, and distributed systems	1.362732297	1.1666667
Databases	1.420191201	1.1
Mathematical foundations	1.038177107	0.9
Programming languages and compilers	0.924412722	0.8571429
Scientific computing	1.710970313	1.0666667
Software engineering	1.273047751	1
Theory of computation	1.203231244	0.8333333

Mean and median author position in author list



Authors are listed by their relative contributions to a publication, therefore, looking at the position a female author is in can provide information on well that author's overall contribution to the field. It seems as if female authors in the programming languages and compliers field appear higher on average, than all the other fields, although mathematical foundations and algorithms and data structures are both fields where women appear higher on the list as well. On average, women appear lower on the list in the scientific computing field.

Conclusion

Men vastly outnumber women in computer science and that is likely to be the case for many years into the future. My project couldn't find any evidence, however, that women tend to publish in different computer science fields than men. In fact, the data showed that there was nearly no difference in their fields of publication.

Women tend to write multiple publications over their careers. The publications themselves tend to be around 10 pages in length with a small number of collaborators. Female authors tend to appear near the top of the collaborator's list.

While there is no field in computer science that women are the dominant contributors, I believe that my data shows that while we women are a small part of the community, we are active and contributing to all areas of study.