Patent Equity | MIT Collaboration Data Analysis

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December 1, 2021

1 Introduction

For the project of MIT Patent Equity Analysis, the main data source is the Faculty Research Collaboration Tool[1], provided by MIT as a website. MIT provides this online database containing the data of its faculties, including the basic information including name, department, professional title; along with the number of articles they have published, the number of conference proceedings, grants, and the number of patents associated with each professor.

In this project, the main goal is to see if there is a correlation between the numbers, also if the race, gender, or tenure status of the professor makes any difference. We also wonder if race or gender has any impact on the numbers.

We have made several steps to reach the final result. First of all, to get the data ready to use in the analysis, we chose to scrape all information needed for analysis from the website.

2 Data Preprocessing

2.1 Web Scraping

In order to obtain the number of articles, conference proceedings, grants, and patents, we scrape the website of the collaboration tool. We first looked at the web page source code using the Chrome Developer Tools, and tried to call the get method from the Python library requests to generate a json file for further data analysis. However, this approach fails due to insufficient information returned. We can get correct numbers for articles, conference proceedings, and grants, but missing data of patents number. However, we found out that we can get the department ids and their associate professor ids using this method.[2]

After several trials on different methods, we finally decided to use the post method of requests, iteratively obtain the HTML source code of each professor, and find the data we need from the source code.[3]

Before we start scrape the website, we took a look at the faculty profile page of each department, and finds out that some departments do not necessarily have the patents or grants number. Thus, we only include the departments of engineering and natural sciences. As a result, we include 13 departments and 692 faculties in our initial faculty dataset.

[1] http://collaboration.mit.edu/
[2] Code see ./code_data/code/web_scraping_id.py
[3] Code see ./code_data/code/web_scraping_main.py

2.2 Gender Classification

Since we do not have gender information in the online database, we decided to find a large database of first names and their corresponding gender to perform classification training to obtain a model. The database we used for training is a Gender by Name Data Set provided by the University of California, Irvine, Center for Machine Learning and Intelligent Systems (UCI).[4] In this dataset, there are 147269 rows, with 4 columns including first name, gender, count, and the probability. We used the first name and gender from this dataset, split them into training set and testing set with the same size after vectorization, then trained them with several different classification algorithms. See Table 1 below for the accuracy scores.[5]

Classification Algorithm	Training Accuracy	Testing Accuracy
Multinomial Naive Bayes	94.71%	58.01%
Bernoulli Naive Bayes	61.82%	61.64%
Random Forest	61.36%	61.44%

Table 1: Training and testing accuracy scores of algorithms used.

As we can see, the testing accuracy scores of all three algorithms do not have a big discrepancy, that the difference between best score and the worst score is only 3.63%. But if we look at the training accuracy scores, the result of the multinomial NB classifier has a significantly higher accuracy score than the other two classifiers. Thus, we decided to use the classifier which uses the multinomial NB algorithm to classify the gender of the MIT faculties.[6]

2.3 Race Classification

For the same reasons mentioned in the previous section, we do not have the race information of each faculty. To classify the race, we refer to the API released by the United States Census Bureau. This database contains 151671 rows and 11 variables in total. Among the variables, I chose the surname, 2PRACE, AIAN, API, BLACK, HISPANIC, and WHITE which are the races from the database, to train the classification model.[7]

We first tried to match the surnames in our faculty dataset with the surnames in the US Census database. The result turns out that 506 faculty surnames are included in the database, and 186 the faculty surnames are not included in the database.

[4] https://archive.ics.uci.edu/ml/datasets/Gender+by+Name
[5] Code see ./code_data/code/gender_classification.ipynb
[6] Data see ./code_data/data/faculties_with_gender.csv
[7] See variable description here: https://api.census.gov/data/2000/surname/variables.html

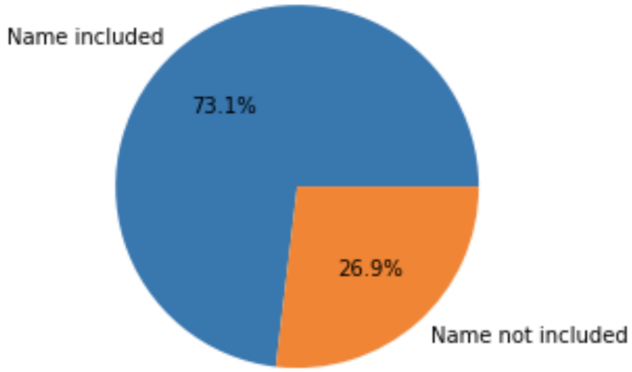


Figure 1: The pie chart of percentage names included in the database.

As we can see from Figure 1 above, 73.1% of the names matched, and 26.9% were not matched in the surname-race database. Thus, we split the surnames into two parts: for the surnames that are matched in the database, we simply assign the race with the highest percentage given in the race attributes, while for the surnames that are not matched in the database, we trained a classification model and apply the model on them.

In the model training step, we extract the surname as the data X and the corresponding race with the highest percentage possibility as the label y. After vectorization, we split the dataset into training and testing sets and applied the Multinomial Naive Bayes algorithm first since it has the best performance in our previous model. The result turns out to be surprisingly good, with a training accuracy score of 85.72% and a testing accuracy score of 86.33%.[8] After classification on race, we merge this result into the dataset with gender classified.[9]

2.4 Year of Publication

Since we need to answer the question of disparity over time, we would like to get the information of the year when the articles were published, when the conference proceedings were held, when the grants were given, and when the patents were published. We found out that on the website there are specific years and dates under each specific work. Thus, we also obtain a dataset containing the years for each faculty, along with the count of each category.[10]

[8] Code see ./code_data/code/race_classification.ipynb
[9] Data see ./code_data/data/faculties_gender_race.csv
[10] Data see ./code_data/data/faculties_gender_race_year.csv

2.5 List of Department

Since we found out that in some departments, the faculties do not necessarily have patent or grant works, to reduce the possible skewed distribution, we decided to eliminate those departments. Here is the list of departments included in our analysis:

- Aeronautics and Astronautics
- Biological Engineering
- Biology Brain and Cognitive Sciences
- Chemical Engineering
- Chemistry
- Civil and Environmental Engineering
- Electrical Engineering and Computer Sciences
- Materials Science and Engineering
- Mechanical Engineering
- Media Arts and Sciences
- Nuclear Engineering
- Physics

3 Preliminary Analysis

3.1 Preliminary Analysis by Gender

The gender distribution of the whole dataset is shown in the graph below, and we analyze the gender associated with all the heads in the dataset.

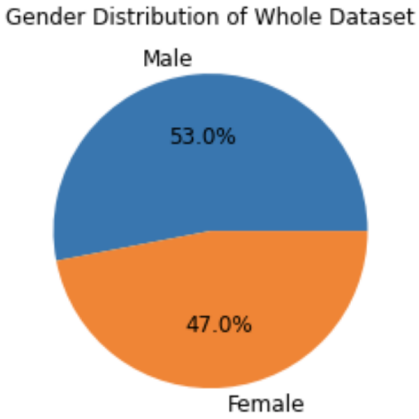


Figure: The pie chart of percentage genders distributed in the database.

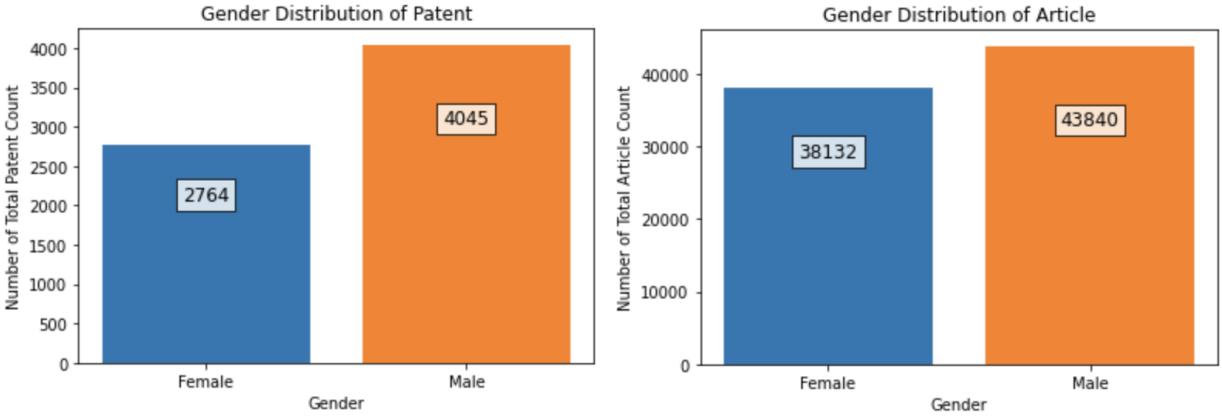


Figure: The bart chart of the distribution of gender in number of Patents and Articles

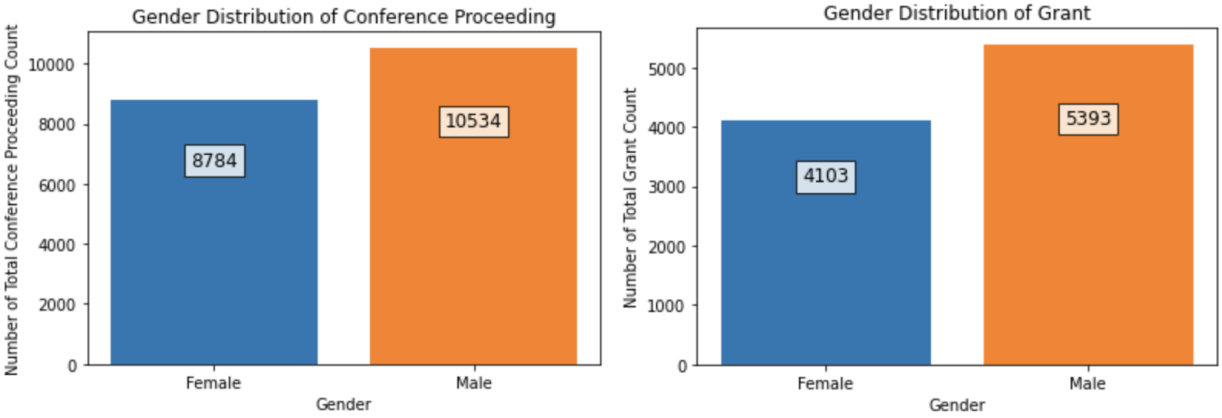


Figure: The bart chart of the distribution of gender in number of Conferences and Grants

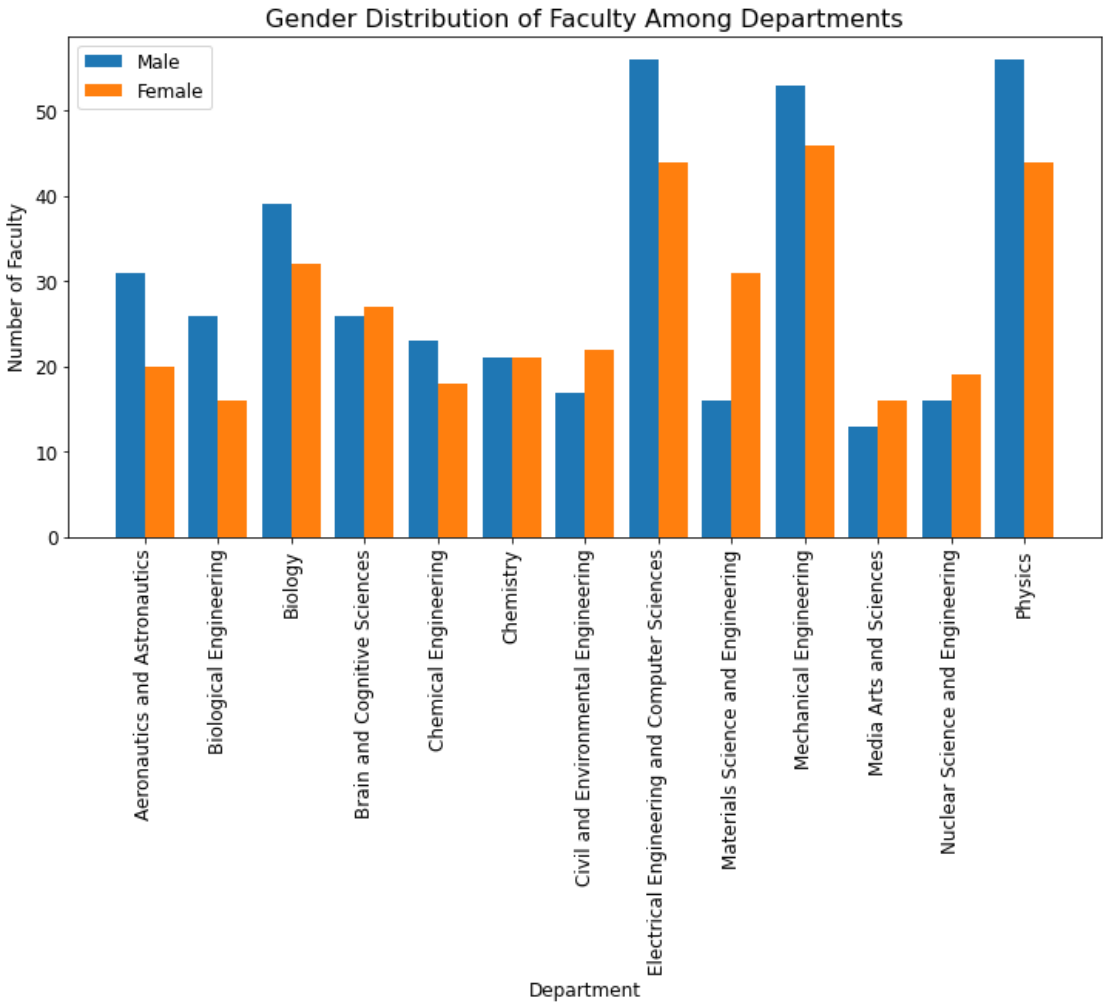


Figure: Gender distribution by gender and by the department.

Based on the graphical analysis based on the whole dataset by gender, by department, and by gender per department, we found out that there's an apparent comparison between the female and male results in all 4 categories, article, patent, grant, and conference proceeding, that we have looked at.

On an overall basis, the male has a comparatively larger number of people than females, but the difference in each department varies, as the graph right above shows.

3.2 Preliminary Analysis by Race

In general there are four types of race in the dataset: 'API', 'WHITE', 'HISPANIC', 'BLACK'. According to the US Census Bureau[11], the four races stand for as following:

API	Non-Hispanic Asian and Native Hawaiian and Other Pacific Islander Alone
WHITE	Non-Hispanic White Alone
HISPANIC	Hispanic or Latino origin
BLACK	Non-Hispanic Black or African American Alone

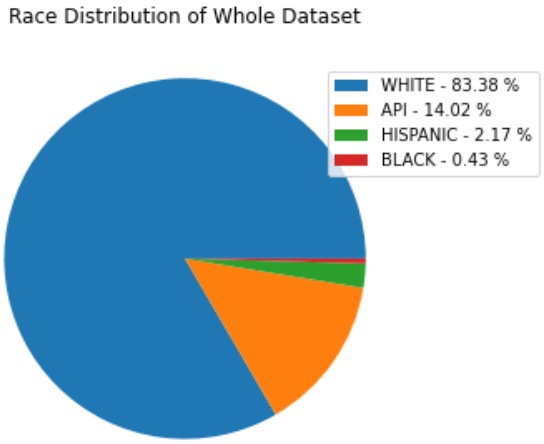


Figure: The pie chart of percentage races distributed in the database.

Similar to gender, we analyze the race associated with all the heads in the dataset.

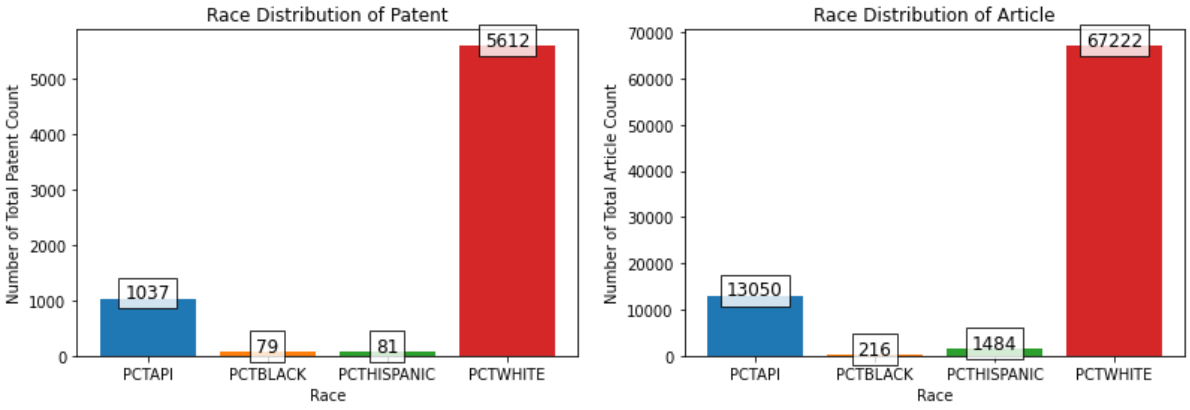


Figure: The bart chart of the distribution of race in number of Patents and Articles

[11] https://api.census.gov/data/2000/surname/variables.html

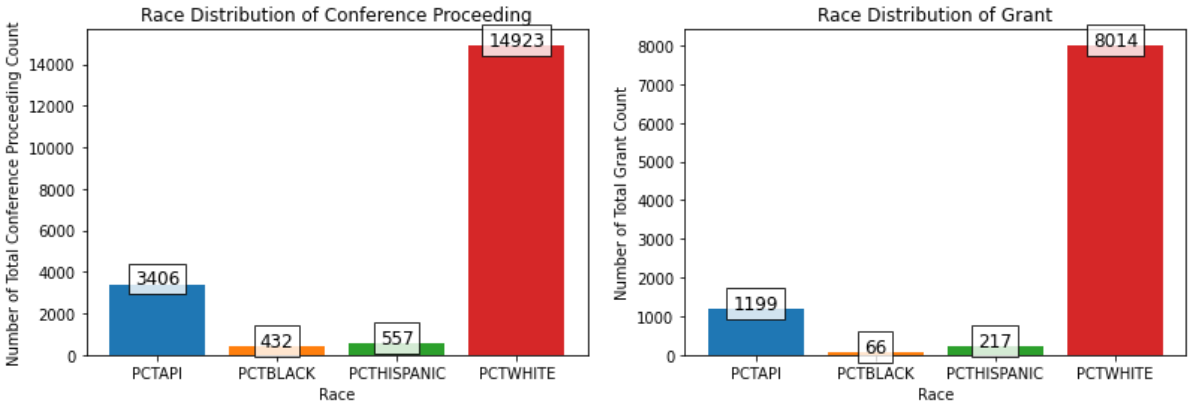


Figure: The bart chart of the distribution of race in number of Conferences and Grants

In general, WHITE weighs the most in all aspects of race analysis. The sum of three other races is approximately one-third of the WHITE.

4 Statistical Disparity Significance

To answer the first analysis question, we looked at the disparity between gender and among races respectively overall at MIT. We first computed the distribution to see if they have a similar shape, and then check the variance equality. If we obtain a result that the variances of two groups are equal, we then perform a hypothesis test using a t-test.

All the tests are performed at the significance level $\alpha = 0.05$.

4.1 Statistical Test - Disparity over Gender

The hypothesis tests have the following hypotheses:
H_0: The means of the two groups are the same.
H_1: The means of the two groups are significantly different.

4.1.1 Article Count by Gender

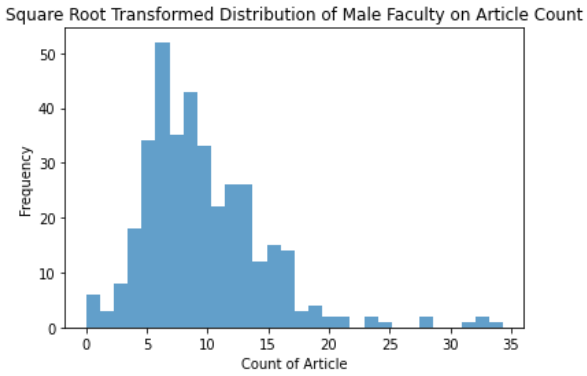


Figure 2: Histogram of Article Count of Male Faculty

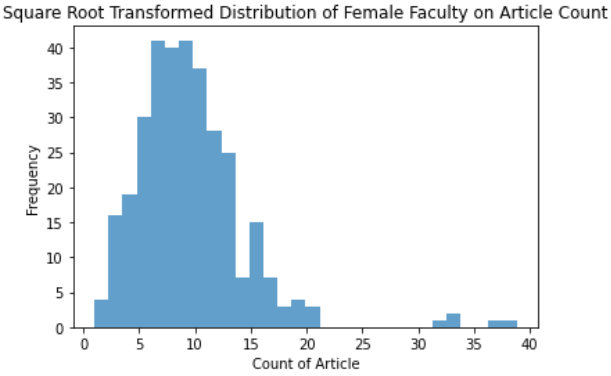


Figure 3: Histogram of Article Count of Female Faculty

The distributions show that the counts of articles for male and female faculties are in a similar shape. Since the distribution plot on raw data does not follow a normal distribution, we transform the data with square root and obtain normally distributed samples. Performing the Levene test on the square root transformed data, we got the result $p - value = 0.43 > \alpha$. We can conclude that the two groups have equal variances.

Performing the t-test, we got the result $p - value = 0.81 > \alpha$. At $\alpha = 0.05$ level of significance, we fail to reject the null hypothesis, that there is no evidence showing a significant disparity between male and female faculties in the total patent count.

4.1.2 Conference Proceeding Count by Gender

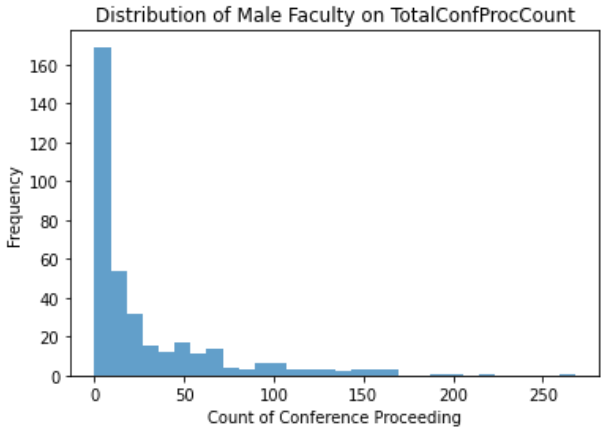


Figure 4: Histogram of Conference Count of Male Faculty

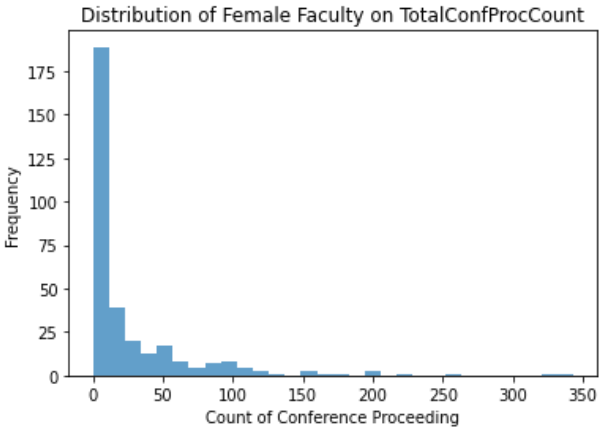


Figure 5: Histogram of Conference Count of Female Faculty

The distributions show that the counts of conference proceedings for male and female faculties are in a similar shape. Even though the distributions are not normal, we fail to transform them into a normal distribution. Performing the Levene test, we got the result $p - value = 0.81 > \alpha$. We can conclude that the two groups have equal variances.

Performing the t-test, we got the result $p - value = 0.62 > \alpha$. At $\alpha = 0.05$ level of significance, we fail to reject the null hypothesis, that there is no evidence showing a significant disparity between male and female faculties in the total conference proceeding count.

4.1.3 Grant Count by Gender

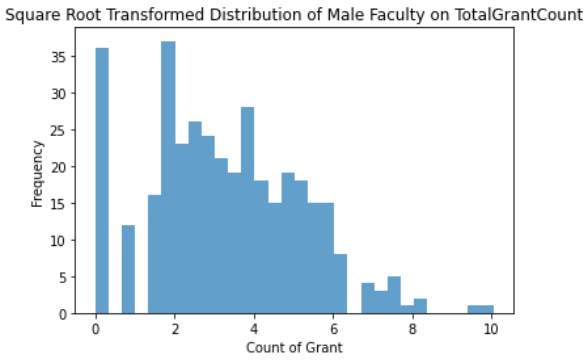


Figure 6: Histogram of Grant Count of Male Faculty

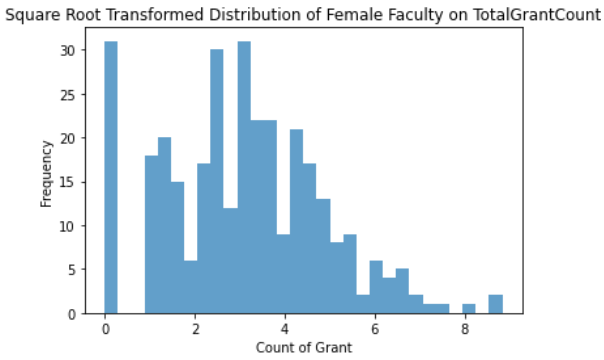


Figure 7: Histogram of Grant Count of Female Faculty

The distributions show that the counts of grants for male and female faculties are in a similar shape. Since the distribution plot on raw data does not follow a normal distribution, we transform the data with square root and obtain normally distributed samples. Performing the Levene test,

we got the result $p - value = 0.066 > \alpha$. We can conclude that the two groups have equal variances.

Performing the t-test, we got the result $p - value = 0.106 > \alpha$. At $\alpha = 0.05$ level of significance, we fail to reject the null hypothesis, that there is no evidence showing a significant disparity between male and female faculties in the total grant count.

4.1.4 Patent Count by Gender

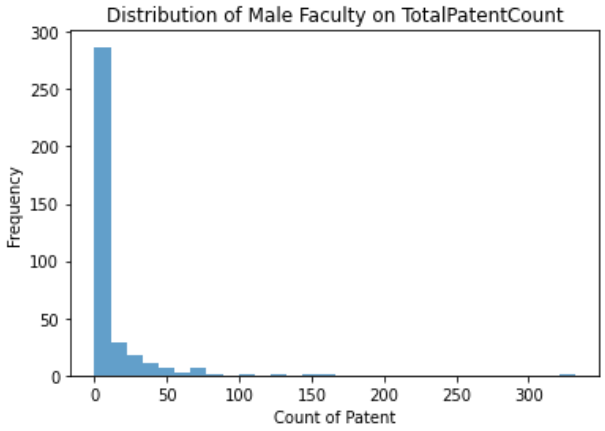


Figure 8: Histogram of Patent Count of Male Faculty

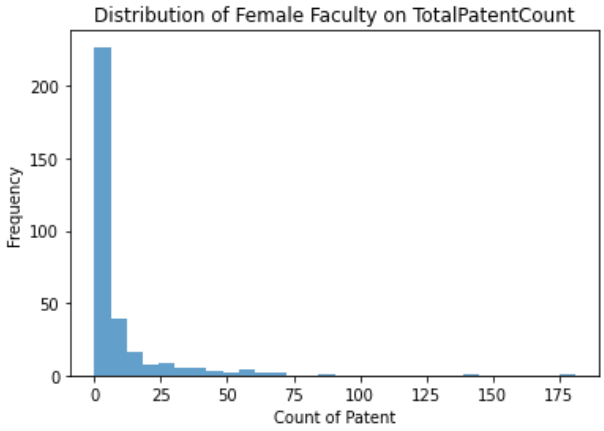


Figure 9: Histogram of Patent Count of Female Faculty

The distributions show that the counts for male and female faculties are in a similar shape. Even though the distributions are not normal, we fail to transform them into a normal distribution. Performing the Levene test, we got the result $p - value = 0.18 > \alpha$. We can conclude that the two groups have equal variances.

Performing the t-test, we got the result $p - value = 0.15 > \alpha$. At $\alpha = 0.05$ level of significance, we fail to reject the null hypothesis, that there is no evidence showing a significant disparity between male and female faculties in the total patent count.

4.2 Statistical Test - Disparity over Race

The hypothesis tests have the following hypotheses:
H_0: The means of all sample groups are the same.
H_1: At least two of the means in all sample groups are significantly different.

In this part of the test, we chose to use ANOVA F-test since there are more than 2 groups of data. Even though we utilized all races in the database, it turns out that only 4 races are matched and

predicted in our faculty dataset. Thus, for all tests below, there are 4 groups of data each representing a distinct race class.

4.2.1 Article Count by Gender

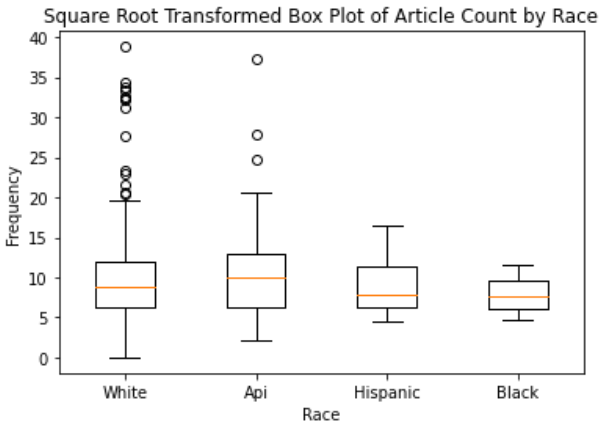


Figure: Box Plot of Article Count by Race.

As the box plot shown above, we can see that the range of all 4 races is quite similar in terms of boxes. However, we noticed there are plenty of "outliers" detected in the race group WHITE and API. This is the result of a large difference between the number of samples we have in each race. Performing the Levene test, we got $p - value = 0.74 > \alpha$. We can conclude that the two groups have equal variances.

Performing the Analysis of Variance (one-way ANOVA), we got the $p - value = 0.55 > \alpha$. At $\alpha = 0.05$ level of significance, we fail to reject the null hypothesis, that there is no evidence showing any two of the races have a significant disparity in the total patent count.

4.2.2 Conference Proceeding Count by Race

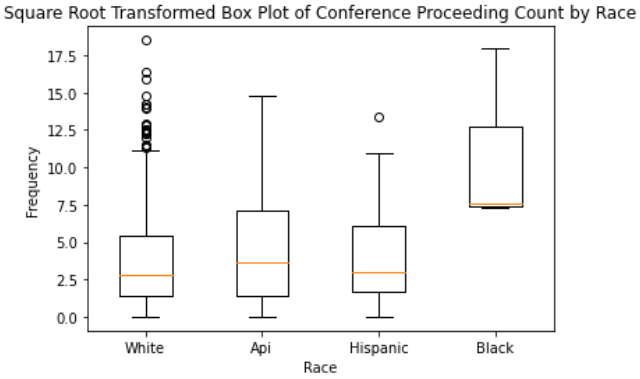


Figure: Box Plot of Conference Proceeding Count by Race.

As the box plot shown above, we can see that the range among WHITE, API and HISPANIC is quite similar in terms of boxes, while the BLACK class has a relatively higher median compared to others. It is obvious to see a lot of outliers detected in the race class of WHITE. This is the result of a relatively bigger sample compared to other races. Performing the Levene test, we got $p - value = 0.33 > \alpha$. We can conclude that the two groups have equal variances.

Performing the Analysis of Variance (one-way ANOVA), we got the $p - value = 0.00063 < \alpha$. At $\alpha = 0.05$ level of significance, we can reject the null hypothesis, that there is evidence showing at least two of the races have a significant disparity in the total patent count.

Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
PCTAPI	PCTBLACK	6.3064	0.0113	1.0453	11.5674	True
PCTAPI	PCTHISPANIC	-0.0776	0.9	-2.5676	2.4124	False
PCTAPI	PCTWHITE	-0.8425	0.1236	-1.8274	0.1424	False
PCTBLACK	PCTHISPANIC	-6.384	0.0203	-12.0601	-0.7079	True
PCTBLACK	PCTWHITE	-7.1489	0.0024	-12.3439	-1.9539	True
PCTHISPANIC	PCTWHITE	-0.7649	0.8142	-3.1121	1.5823	False

Table: Pairwise Comparisons of Means in Conference Proceeding Counts.

The table above shows the pairwise comparisons between each race. We can see that there are significant disparities between BLACK and API, between BLACK and HISPANIC, and between BLACK and WHITE. And for the rest pairs, we fail to reject the null hypothesis, that no significant disparity exists.

4.2.3 Grant Count by Gender

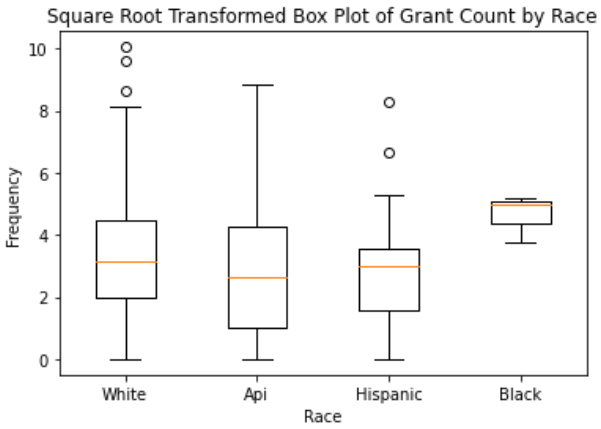


Figure: Box Plot of Grant Count by Race.

As the box plot shown above, we can see that the range of WHITE, API and HISPANIC is quite similar in terms of boxes, while BLACK is slightly higher than others in terms of the median. Performing the Levene test, we got $p - value = 0.097 > \alpha$. We can conclude that the two groups have equal variances.

Performing the Analysis of Variance (one-way ANOVA), we got the $p - value = 0.116 > \alpha$. At $\alpha = 0.05$ level of significance, we fail to reject the null hypothesis, that there is no evidence showing any two of the races have a significant disparity in the total patent count.

4.2.4 Patent Count by Gender

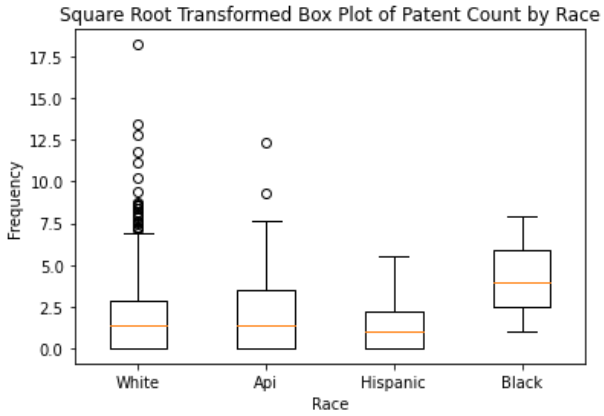


Figure: Box Plot of Patent Count by Race.

As the box plot shown above, we can see that the range of WHITE, API and HISPANIC is quite similar in terms of boxes, while BLACK is slightly higher than others in terms of the median. Performing the Levene test, we got $p - value = 0.598 > \alpha$. We can conclude that the two groups have equal variances.

Performing the Analysis of Variance (one-way ANOVA), we got the $p - value = 0.28 > \alpha$. At $\alpha = 0.05$ level of significance, we fail to reject the null hypothesis, that there is no evidence showing any two of the races have a significant disparity in the total patent count.

4.3 Answer to the First Analysis Question

To conclude the statistical tests performed above, we fail to reject the null hypothesis for all tests by gender. That is, according to our tests, we found that there is no statistically significant disparity between male and female faculties in all four categories we examined.

For the tests by race, we only successfully reject the null hypothesis for the conference proceeding count and fail to reject the rest three categories. That is, we found that there is no statistically significant disparity among races in articles, grants, and patents; there is a significant disparity for conference proceedings.

5 Disparity Over Time

In the previous sections, our team calculates, visualizes, and compares the number of patents, grants, articles, and conferences proceedings in different genders and races. Since female professors are less than male professors, the overall trend of the counts for male professors is more than those of female professors. And it is similar for different races. Even though we did not see a statistically significant disparity in genders and in races except for the conference proceedings by race, we still want to see an overall trend of the counts over time. In addition to the trend constructed using raw numbers, we put the disparity index into account this time in order to offset the influence of the raw data and reveal the fact that individual genders/ races contribute.

5.1 Disparity by Gender

In this part, we first clean and consolidate the data we have. We eliminate duplicates-- professors who are counted in more than one department but are the same professors. We also delete outliers in the "Year" parameter, which are "No Issue", "1", "2", "Supp1", and "First Serie.1".

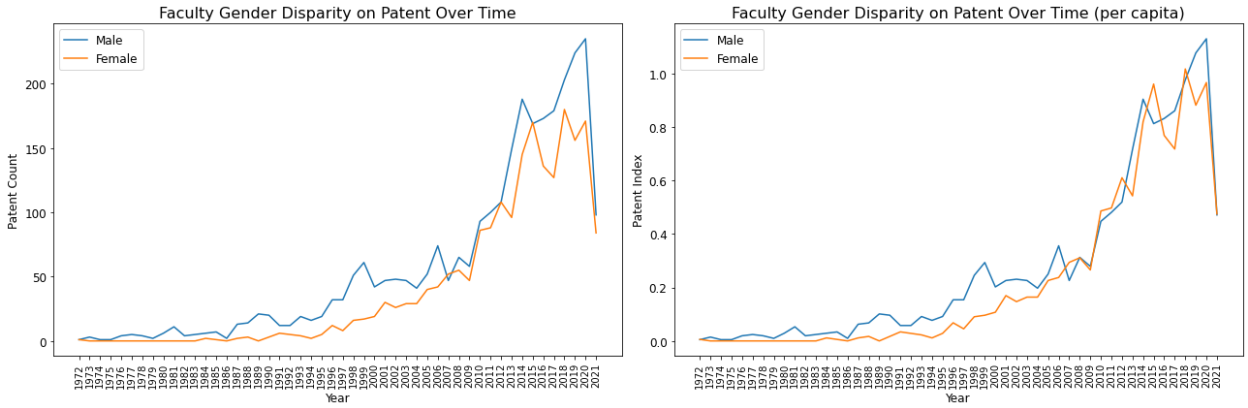


Figure: Patents Count for professors of different genders (without and with disparity index)

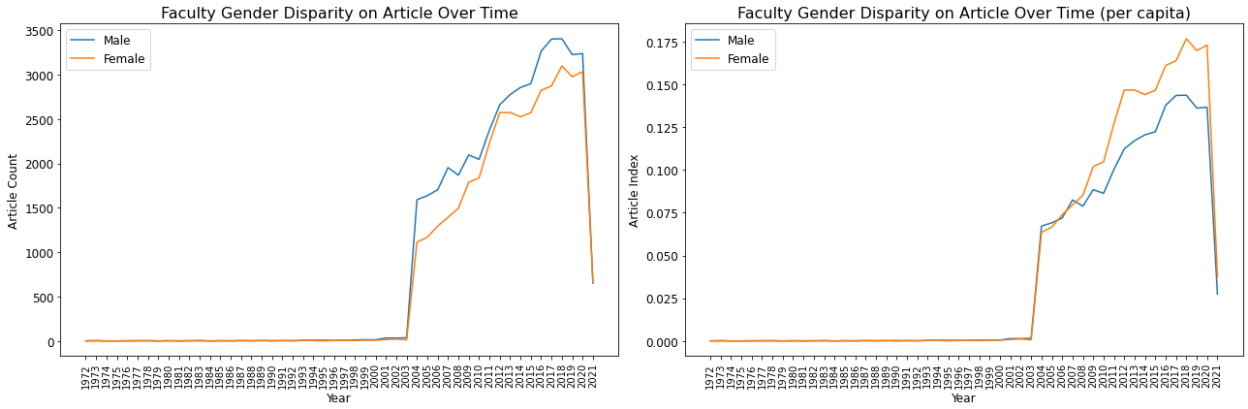


Figure: Articles Count for professors of different genders (without and with disparity index)

There has been an extreme jump in count since 2003, and that might be due to the reason that there is only a limited number of articles recorded on the website. We can see that even though the raw number shows male faculties having an overall larger count than females, the situation reverses in the per capita graph.

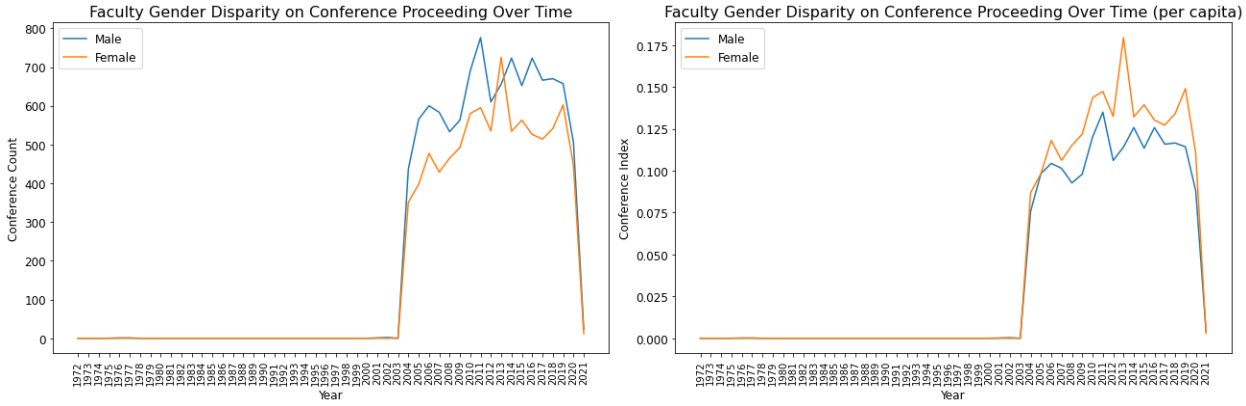


Figure: Conferences Proceedings Count for professors of different genders (without and with disparity index)

Here we can see for a very long time period there's nearly no record on the conference proceeding, and it might be due to the technical issue that those years the faculties faced. The internet was not as convenient as nowadays, and there might not have a standard process to record the conferences before 2003.

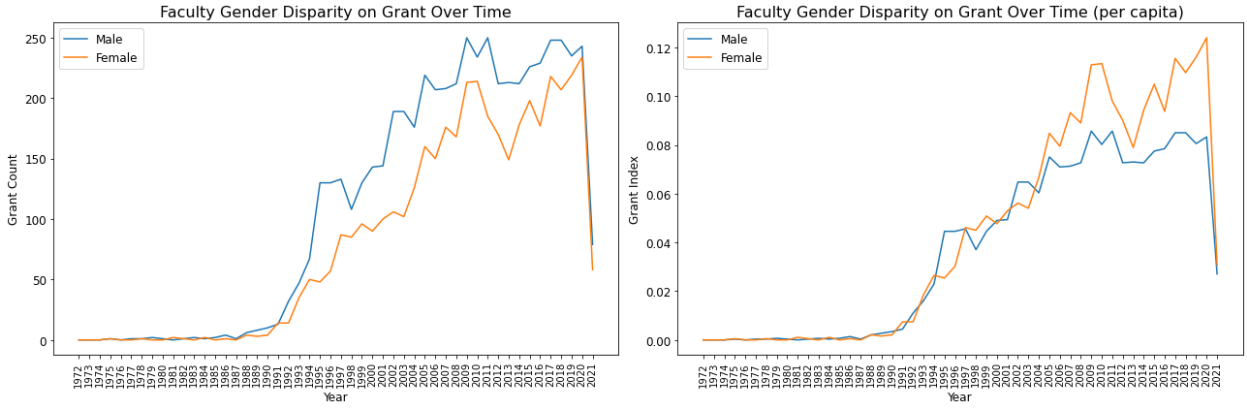


Figure: Grants Count for professors of different genders (without and with disparity index)

Put disparity index into account when we consider whether different genders can exert influence on the result. The overall trend does not change because of the disparity index, but we can see that the differences in the number of grants between male and female professors become smaller.

Before considering the disparity index, the picture shown indicates that male professors have more article counts, but after dividing the article count by each gender's ratio, we can see female professors don't do worse than female professors in terms of the article number they have, and

sometimes even better. It helps reveal the individual contribution each professor has rather than the whole group contributions which could lead to too general conclusions and bias.

Will the change be the same for different races when taking the disparity index into account? Our initial guess is that the situation will become different as WHITE has a large percentage compared to the super low percentage of BLACK. Let's see the actual trending when we consider the disparity index.

5.2 Disparity by Race

Similarly to the disparity by gender, we also remove the duplicates, and remove the invalid years in the dataset, and construct graphs in raw numbers and with disparity index for each category.

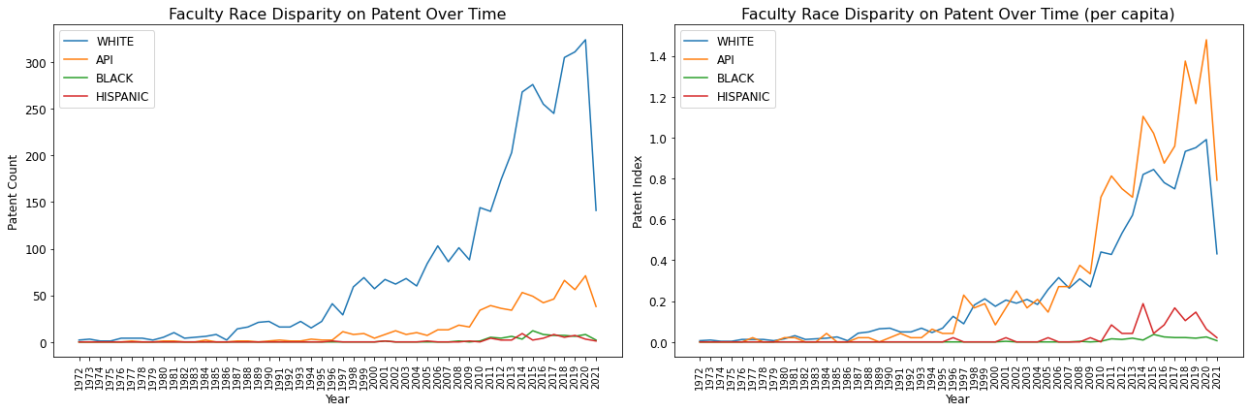


Figure: Patents Count for professors of different races(without and with disparity index)

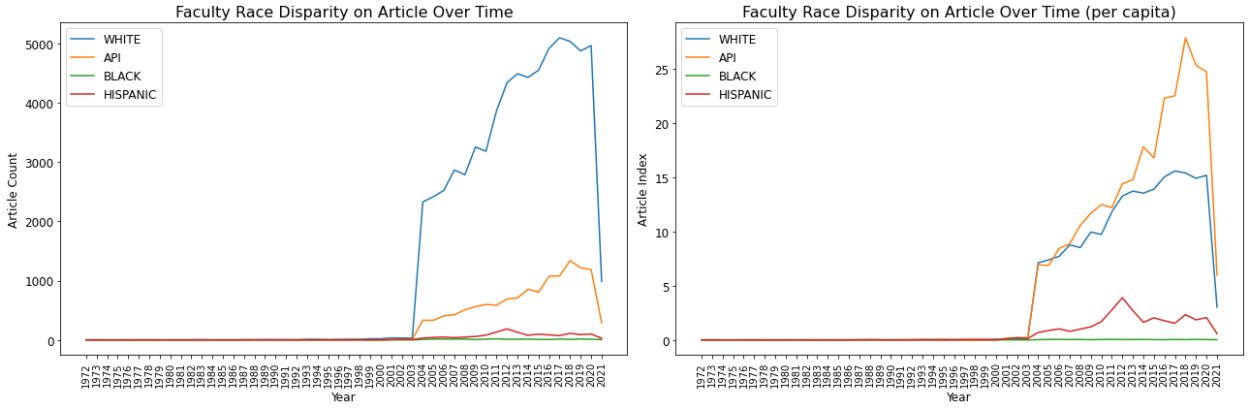


Figure: Articles Count for professors of different races(without and with disparity index)

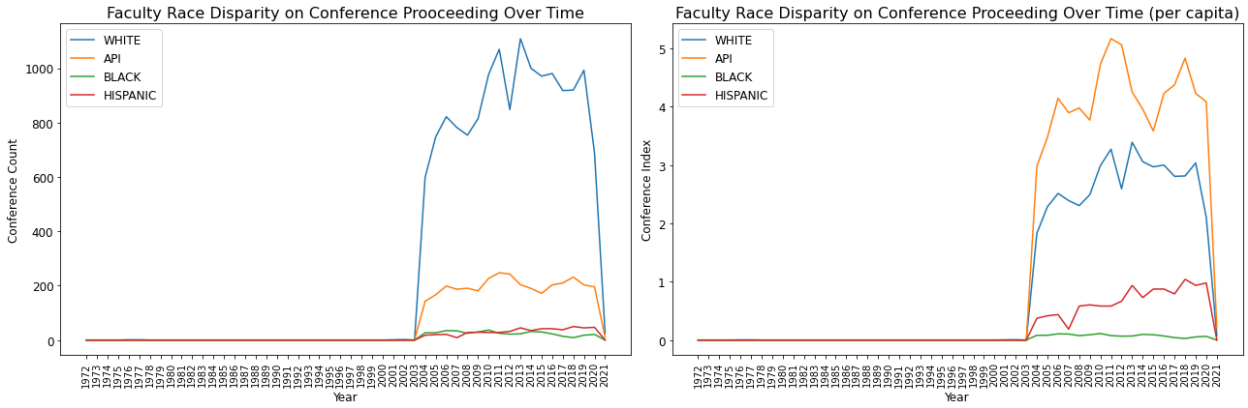


Figure: Conferences Proceeding Count for professors of different races(without and with disparity index)

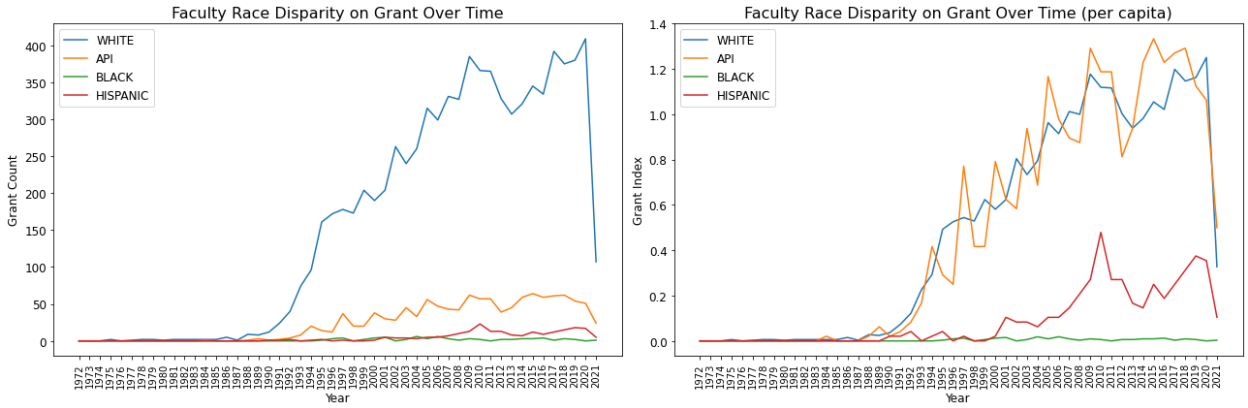


Figure: Grants Count for professors of different races(without and with disparity index)

After using the disparity index, we can see more vivid trending of the races that have very few professors. Especially API professors and BLACK professors, their contributions are shrunk when we use raw data to do data visualization because of their small population bases. In fact, their individual contributions are even larger than WHITE professors. We can see this by comparing the plots of with and without disparity index, and also by comparing the parameter counts of professors of different races from the per capita plot.

6 Gap Between Newer and Older Faculties

6.1 Disparity by Gender

In this section, we are going to focus on how the disparity differs between newer and older faculty groups. Since it takes more than 8 years to become a professor in general, we decided to use the titles of professors to divide whether a professor is new or old. We group faculties with the title “Professor” as older faculties, and the rest, “Associate”, “Assistant”, and “Other”, as newer faculties.

Data of total Rank:

Professor	385
Associate	104
Assistant	80
Other	123

As a result of this classification, we have 385 older faculties, and 307 newer faculties.

Figure: Patent Count for professors of different gender (without and with disparity index)

According to the analysis, the disparity of patent count of different genders for newer professors is bigger than the older professors. The graph of newer professors both general and per capita show a bigger gap between two curves.

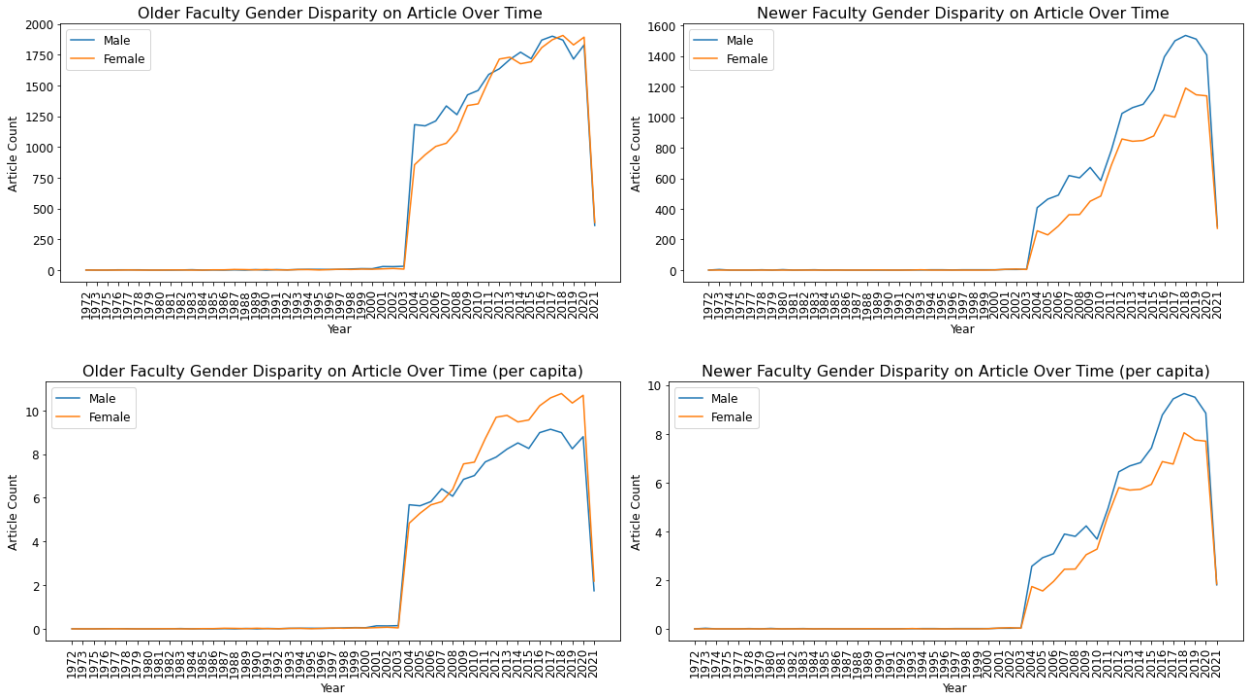


Figure: Article Count for professors of different gender (without and with disparity index)

Similar to patents, the disparity of article count of different genders for newer professors is bigger than the older professors. The general graph is more obviously, compared with the older one, the gap between different genders is enormous.

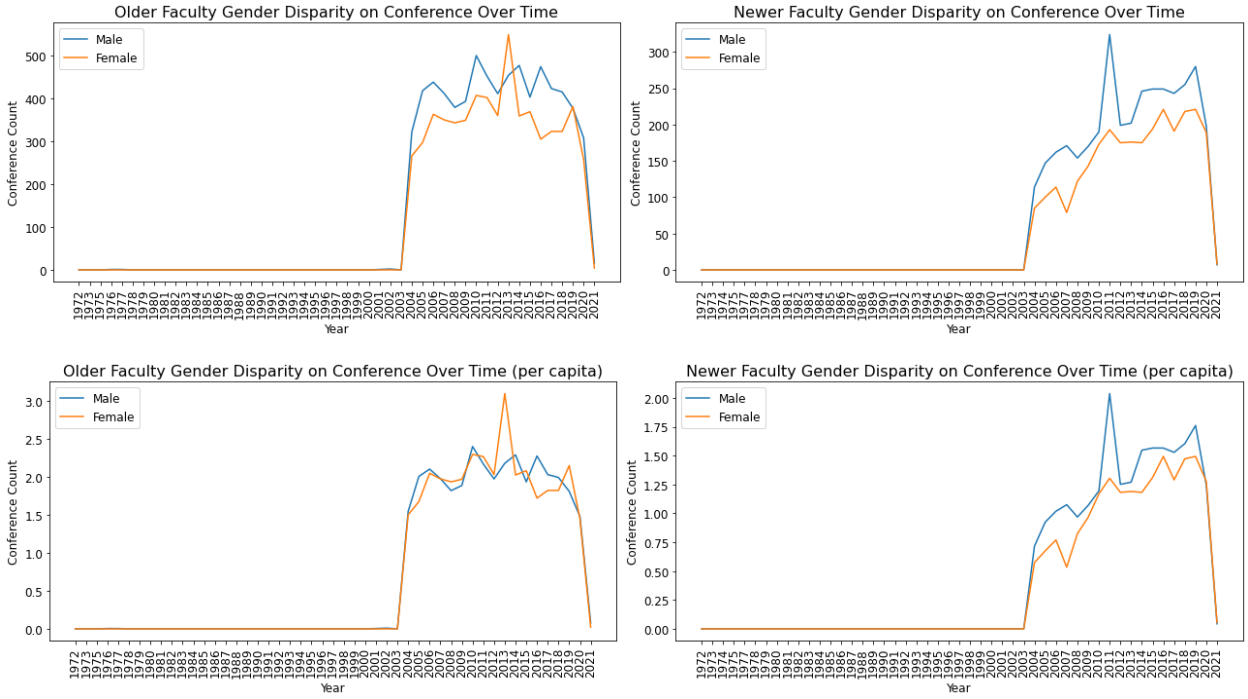


Figure: Conference Count for professors of different gender (without and with disparity index)

Compared with older ones, the graph of newer professors is clear that the disparity between genders is increasing.

Figure: Grant Count for professors of different gender (without and with disparity index)

The disparity in grant Count for professors of different genders of old and new professors is not very big. In graphs the curves are close to each other.

6.2 Disparity by Race

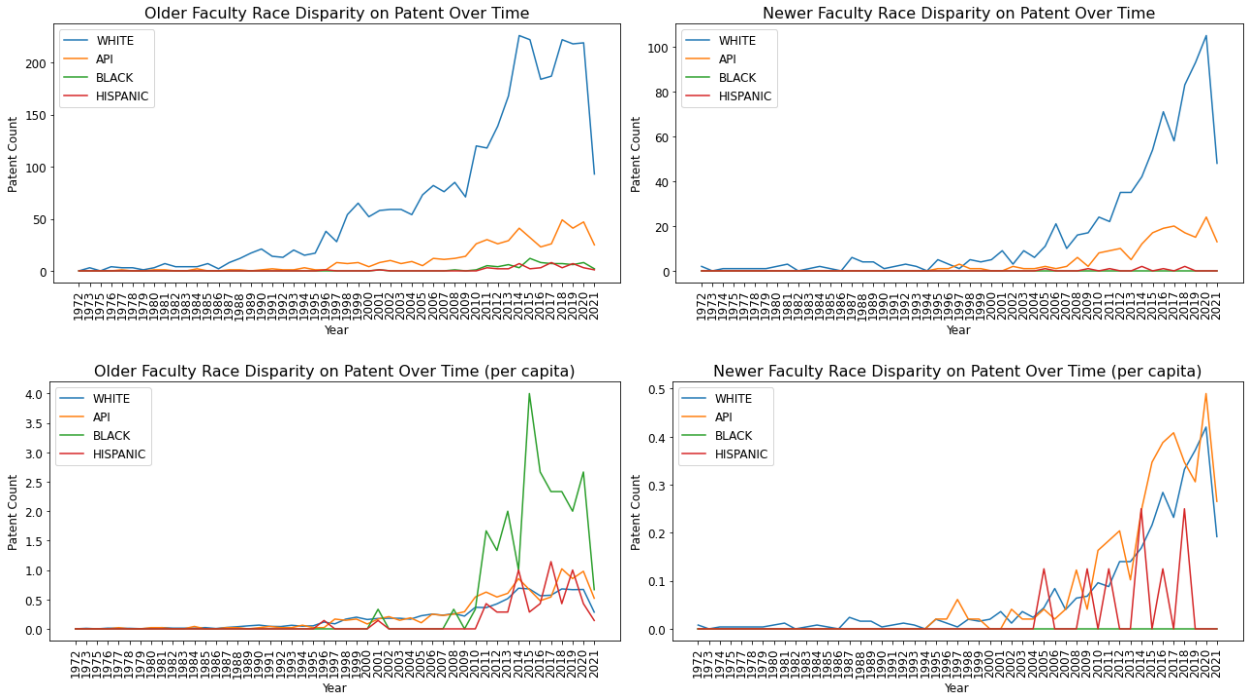
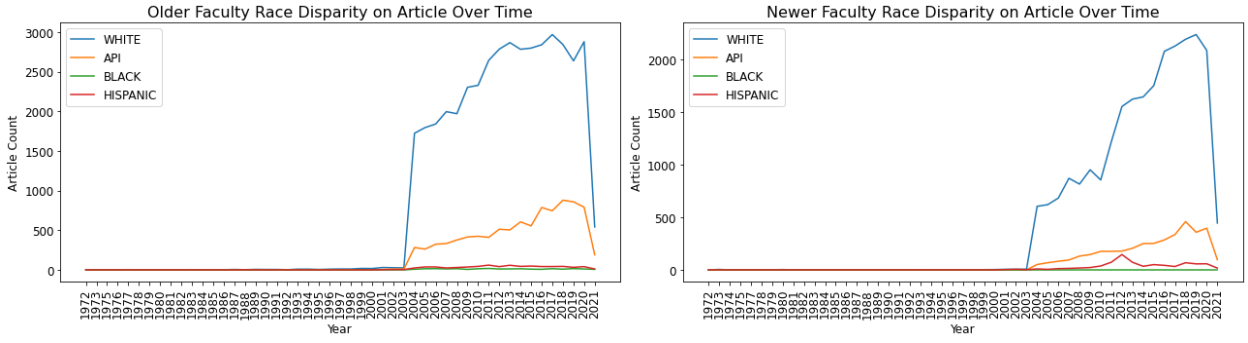


Figure: Patent Count for professors of different races (without and with disparity index)

The disparity of patent count of different races is great in both old and new. For older professors, the disparity starts earlier than new professors. WHITE has a significantly larger count if we look at the graphs constructed by raw numbers, but it is not the case when it comes to per capita data. For older faculties, BLACK has a comparatively larger per capita count especially since 2011, while WHITE and API have the most per capita count in the newer faculty group.



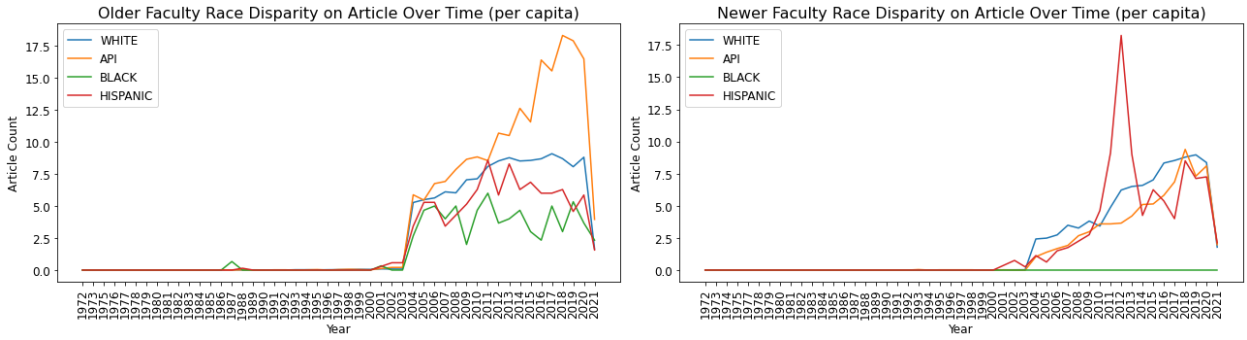


Figure: Article Count for professors of different races (without and with disparity index)

The disparity of article count of different races is great in both old and new. The increasing speed of disparity for newer professors is faster than older professors. The similar situation as the graphs of patents also happen here, that even though WHITE has the most work count in raw numbers, this race does not have an absolute advantage in the per capita count.

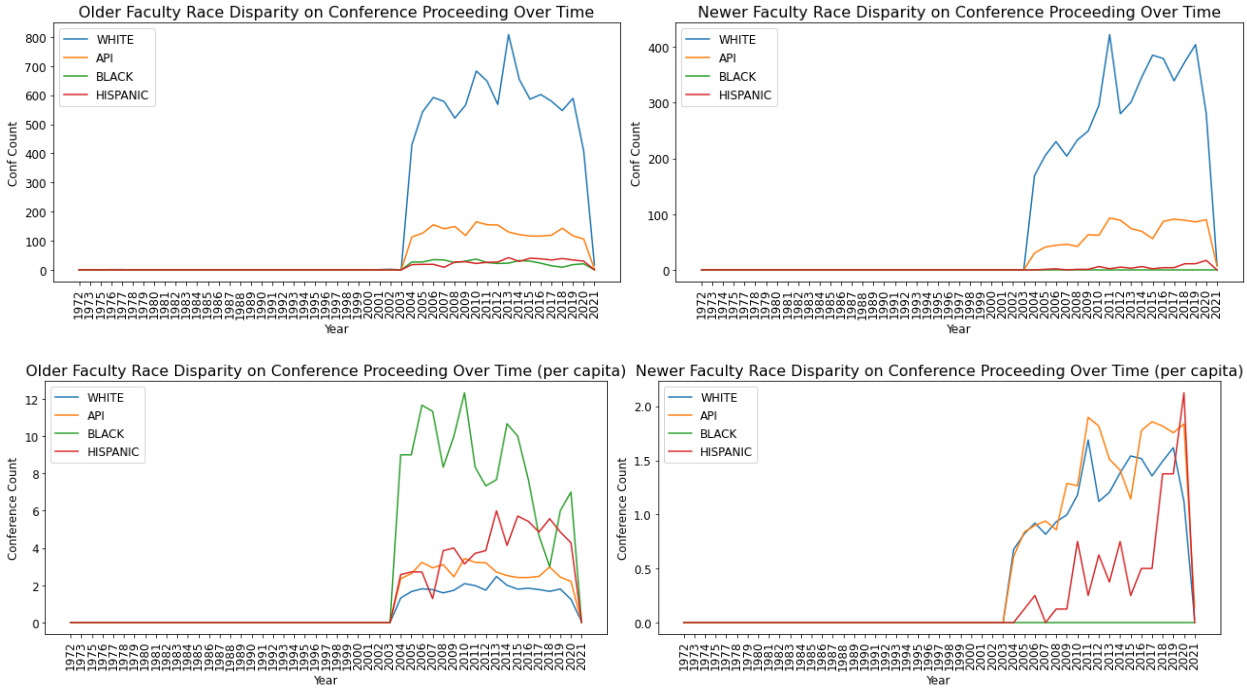


Figure: Conference Count for professors of different races (without and with disparity index)

The disparity of conference count of different races is great in both old and new. The increasing speed of disparity for newer professors is faster than older professors.

Figure: Grant Count for professors of different races (without and with disparity index)

The disparity of grant count of different races is great in both old and new. The increasing speed of disparity for newer professors is faster than older professors. The disparity of newer professors is increasing but the older professors' disparity is decreasing.