Final Project Report

The Freedom Donkeys

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Theme

In this project, we attempted to compare and contrast the common conditions and precursors for discipline in civilian vs. officer reported complaint reports.

Along with this, the data present in the CPDP database would be a good resource to see whether attempts at police reform have been effective over recent years. We can also track whether different categories of allegations have grown to be more reprimanded as time has gone on (and if complaint reports have led to more reprimands over time) and track patterns of which officers are most often disciplined.

CP1: Relational Analytics

Within this checkpoint, we wrote SQL queries to answer 4 main questions we had about the data relating to our theme. The goal of answering these questions is to prepare us for the following checkpoints and acquire some early answers to how the data can be used. Below, we have the four questions and a general analysis of the query.

Q1: What is the number of reprimands for each allegation category?

From our executed query, we can see that the categories with the largest number of disciplines are "neglect of duty", "miscellaneous", and "associated with felon". Out of these three, miscellaneous is non-documented, which is a huge limitation of this dataset. It may be helpful to look into these allegations to see if all of them are actually miscellaneous in future CPs, such as the NLP CP. Thus, it is hard to see the effectiveness of police reform since many allegations are not clear from this database.

Q2: Which categories have seen the largest percentage increase in reprimands as time has gone on?

We explored the difference in percent reprimands for each category over a period of ten years (between 2000-2010). After running our analysis, we found that the "Inadequate / Failure to Provide Service" allegation has risen 5.54%, the most over the selected ten years. Oppositely, the "Slow / No Response" allegation has dropped by 2.77% during the same period.

In terms of tracking police reform over time, it is not a good sign that the magnitude of the largest percent increase is twice the magnitude of the largest decrease. Additionally, “Failure to Provide Service” as an increasing allegation can be concerning considering the increase in police spending over the 10 years. Similarly, “Slow / No Response” as the decreasing allegation is not necessarily a good thing if the police response is not helpful or detrimental to the public.

Q3: How has the difference between the number of department and civilian complaints changed for different categories over time?

Using our calculated values, we can see that for most categories, the difference between civilian and officer complaints has seemingly decreased. However, this is mostly due to a lack of recent data so it seems like there were more complaints in the past. For example, the difference in "Use of Force" complaints dropped from 1174 in 2001 to 133 in 2017. "False arrest" complaints similarly dropped from 98 to 83 in the same time period. Thus, these results tell us that we cannot use the difference in department and civilian complaints over certain years to make accurate observations. This is one of the biggest hurdles in attempting to track complaints over time using the CPDB. Instead, we can continue to do an analysis like in Q2 where we compare the percentages so each allegation category is only compared to the total number of allegations for that year.

Q4: How do the number of civilian/police reprimands differ in relation to the number of allegations for specific "problem areas"?

With our current SQL query, we find the number of officer and civilian complaints for each beat. In the table below, there are the highest three and lowest three beats in terms of civilian and officer complaints. You can see based on the data that there is very little overlap between the beats that have the highest number of civilian complaints and the number of officer complaints. This could mean that the areas where civilians have the most problems with police are not the same as where police think the most problems occur.

However, the numbers are not normalized by population so naturally, in areas with a larger number of civilians, there are bound to be a larger number of civilian complaints. The next step will be to identify actual "problem" areas and compare those specifically or track the differences over time to see if there has been a change in what areas report the largest number of complaints.

Table 1. Beat ID for highest number of officer / civilian complaints.

Beat ID	Number of Officer Complaints	Beat ID	Number of Civilian Complaints
160	820	2	1773
132	586	132	1532
261	464	261	1477
32	2	54	23

CP2: Data Exploration

In this checkpoint, we mapped some of the data we got from CP1 to different graphics to get a better view of what it says. For both questions, we split it into two different charts to measure the data for civilian and police reported complaints separately. You can view the corresponding visualizations for the following questions in Appendix A.

Q1: What is the relationship between the number of officers disciplined in each category of allegation for police/civilian reports?

With our two pie charts, we explored what allegation categories officers were reprimanded for when a civilian reports them versus an officer. Using this data, we try to observe if there is a difference between what allegations are disciplined and if it depends on whether or not a civilian filed the complaint.

Based on our charts, you can see that several of the largest categories for both police and civilian complaints match up. As such, if you pull up the Tableau files, you'll see that the four largest categories (Operation/Personnel Violations, Use Of Force, Conduct Unbecoming, Lockup Procedures) are approximately the same for both sides. Thus, you can potentially gather that there are officers filing complaints who have the same mindset that the civilians do; they recognize some of the corruption that is present within the CPD. However, since we are using the allegation category instead of the allegation name, we lose a lot of potential data or correlations there.

Q2: How does the number of officer disciplines change for each area (per 1000 people) in Chicago for civilian/police allegations?

For this question, we wanted to gain insight into whether more allegations tend to appear in certain areas for both civilian and police allegations. The data shows that for civilian allegations AND for police allegations, area_id 1549(district 1) has the largest number of disciplines per capita. This area also happens to be one of the wealthier areas of Chicago, where the average household income is much higher than everywhere else. This may contribute to more civilian disciplines because police may respond to these civilian allegations more seriously than anywhere else. An alternative explanation is that the population of these areas is relatively low compared to the rest of Chicago. However, there is still a much larger number of people who work in this area and would be around district 1 for other reasons other than living there, which would mean the population data is misrepresenting how bad this area is.

It is difficult to determine why the police disciplines are also highest in that area. Unfortunately, we could not use the information on where police units were deployed to divide the disciplines of police allegations by the police presence in a given area. This is because the police units information does not match up with the civilian areas mapped out using the data_area table.

Future Work

In the future, we might be able to look at the data allegations instead, but we would not be able to use a pie chart due to the overwhelming amount of allegation names. We would need to explore other chart types to find one that can handle a significant amount of nominal values while still allowing for a succinct comparison between civilian and officer complaints.

Additionally, we should try to divide the police disciplines from police allegations by the number of officers deployed to a given area. This would require us to use data_policebeat to find out which beat officers are associated with, and then we can use the area_id foreign key to find where officers are deployed.

CP3: Interactive Visualization

Similarly to checkpoint 2, we created some visualizations to better understand what the raw data was presenting. We created a bar chart race to see which allegation categories were highest for each year from 2000-2017 and similarly split it between officer & civilian allegations. We also created another interactive visualization that allows you to see which officers are disciplined together. This topic is also explored further in CP4.

Q1: Bar Chart Race - Number of [officer]() / [civilian]() allegation reports in each category per year

This question helped us gain insight into whether attempts at police reform have been successful over the past few years and how different problems may have sprung up over time. From both charts, we can see right away that “Operations/Personnel Violations” is the top category for most years, and usually by a wide margin. We can see the charts also show that “Use of Force” has remained a problem in police conduct throughout the past two decades. The prevalence of these two issues fits with what we have come to expect from the PD; use of force is always a hot debate topic and operations violations can encapsulate much smaller issues like owing money to the city (probably the reason for its high ranking throughout the years).

Additionally, drug/alcohol abuse has continued to be a major source of police discipline throughout the past two decades (one of the Top 5 contributors). However, on the police side, we see more complaints that have to do with internal issues such as “Conduct Unbecoming” and “Lockup Issues”. On the other hand, as expected, top civilian complaint categories include items like “False Arrest” and “Illegal Search”. There is also less of a gap between operations violations and the other categories up until the year 2015. Part of this could be due to the fact that some complaints that have been filed in recent years have not yet come to fruition or been made public.

From these charts, it is not clear if police reform tactics have been very effective. Partially because of the lack of data in recent years, but we can see how the complaints have changed and we can see clear trends in what complaints have been more prevalent over the past twenty years. This could inspire future change and pull a focus towards trying to lower these complaints. It might also be interesting to re-run the chart with newer data in 5 or 10 years to observe if the addition of any information will yield a more significant conclusion, especially with police departments undergoing heavy public scrutiny. Additionally, it would be helpful to look at the differences between the “Operations?Personnel Violations” complaints for civilians and officers and observe if they focus on different things or if civilian complaints in this category are more serious than the department complaints.

Q2: Zoomable Circle Packing - Number of officers disciplined together (within the same complaint report via data_allegations.crid)

One trend we noticed across all the decades was that operation personnel violations were the most common reason for disciplinary action. In the 1990-2000 decade there was a violation resulting in 108 officers being disciplined, in 2000-2010 there were 64 officers disciplined for “indebtedness to the city”, and in the 2011-2018 decade there was a violation that resulted in 26 officers being disciplined. It seems that whenever a large number of officers are disciplined together, it is the result of operations violations, not more severe offenses such as use of force or drug/alcohol abuse. These types of disciplines are not trying to be solved by police reform, so it makes sense that they continue to be apparent throughout the past few decades.

Another trend we are noticing is that within complaint reports with 2 parties, a large portion of the reports have one officer with a larger number of disciplines paired with another officer with relatively few disciplines. Some examples of this in the visualization are CRIDs 1050702, 1082951, 1044664 and 1073789 (all in 2011-2018). These types of situations are especially concerning because given the information we learned from Prof. Pappachristos, we know that officers associated with others that have a high number of complaint reports are more likely to end up in complaint reports in the future. One future development may be to watch out for these situations in the future, where an officer with a low number of disciplines is paired with a higher disciplined officer. We should watch out for trends in the number of these bubbles and ensure that as few of them as possible happen.

Future Work

One change we can make to get better data from this visualization is to divide the discipline count by the allegation count to get the portion of sustained allegations for a given officer. This might help us understand whether officers who have a large number of disciplines have simply been around for a very long time or are actually being disciplined more often than their colleagues.

CP4: Graph Analytics

For our model, we ended up creating a node for every officer who has been disciplined by either a civilian or department complaint and mapped an edge between officers on the same crid (complaint report id). We created a graph for civilian complaints and another for officer complaints. From there, we found different triangles and groupings within the graphs and plotted some of the most components that showed up in the graphs. These are shown in Appendix B and referenced below. Our initial question that we were exploring is also written below.

Initial Proposition: For the officers who have been disciplined, we will create a graph where the nodes are the officers and the edges are weighted by the number of complaint reports shared between two officers. We will repeat this for complaint reports who have been disciplined for a civilian complaint and those who have been disciplined from an officer complaint. Finally, we will see if these co-accusal graphs have the same density and/or are similar in cluster formation. We will search for cliques/triangles within this graph to see if there are patterns with which officers are getting disciplined together.

Analysis

Part of our theme involves discovering patterns in what attracts discipline. Here, we study the connected graphs of officers who were disciplined together within the same complaint.

In the figures above, these are chosen because they are the components with some of the highest counts/recurrences. Each node is an officer and each edge is a co-listing on the same complaint, as mentioned previously. The odd numbered figures plot a component with discipline counts taken into account while the even numbered figures following an odd numbered figure indicate the same component except with total allegation counts.

In Figure B.1, we can see that there is not as much interconnectedness besides a small party of officers. From those officers, it seems that a string of officers becomes included into the component. There is one main group of officers who are white (we assume this because the officers who are white have higher allegation counts according to Figure B.2) and it leads to another group of hispanic officers with a small number of allegations against them. However, we can see that despite having less allegations amongst the hispanic officers, they are about equal in discipline counts with the white officers. This could be indicative of a racial bias when disciplining officers or a difference in the severity of complaints when the hispanic officers are involved. Additionally, this could lead us to believe that there is often a

connection between a few 'troublesome' officers which spreads to the officers who fraternize with them.

Finally, we can see in Figure B.3, we have a component from the police complaints graph plotted. Of course, these officers seem to be extremely interconnected, but fall under a broad range of races. There is also a decent difference between the highest and lowest officers in terms of allegation counts according to Figure B.4. We can assume that there exists way more connections between officers for officer complaints because of the type of complaints that are usually filed by the department (Personnel Violations, according to checkpoint 3). Thus, these officers could be ones that are frequently running into the same issues over and over again like being late to work, owing money to the city, etc. However, with civilian complaints, we can actually explore more connections between different officers and the number of complaints that exist between them.

Based on these figures, we can see a big difference between the civilian and police complaints, most likely because of the type of complaints. Additionally, we can conclude that a few 'bad' officers can lead others to more complaints, as described in Figure B.1. There also exists at least a small ethnic influence when you consider the majority white officers that show up in these plots, especially Figure B.2.

Future Work

In the future, you could track specific officers or groups of officers who we have identified as officers that lead to complaints and observe if they lead other officers to more interconnected complaints. Then, by observing these officers, we can find a common denominator and incorporate that into a police reform program. Those observations can also happen now based on past data; by looking at the records of officers within these common components, we can draw conclusions about what behaviors or actions lead to complaints. This is all with the goal of changing the way police officers act in an attempt to reduce the number of complaints received.

CP5: Natural Language Processing

Lastly, we used a topic model on complaint report summaries to see if certain civilian report topics lead to officer discipline more often than others. We also used a keyword based model to see if there was a difference when compared to the topic model. The purpose of this was to determine whether a given complaint report summary topic matches with the reported allegation category. The relevant figures are referenced below in Appendix C.

Civilian Complaints

In Appendix C, Figure C.1 and C.2 show the number of reports with summaries for each allegation category and allegation name. These reports are civilian reported allegations that result in police discipline of at least 1 of the reported policemen, and were used as references for what our topic categories. For topic modeling we used the LDA method. The best LDA model was chosen based on the maximum coherence value, which we found to be 5 topics. The coherence values can be seen in figure C.3.

We can see a subset of the topics generated by the LDA model in figure C.4, and a graph of the word counts of most relevant words can be seen in figure C.5. To see a full list of each word in each topic, see the visualizations at our github repository under the sections seen below.
"checkpoint-5/data/interactive_visualization_lda/ldaModel_civ_vis.html" and
"checkpoint-5/data/interactive_visualization_lda/ldaModel_pol_vis.html".

From the intertropic distance map in figure C.6, we can see that our topics are distinct and unique; there is little to no overlap between the topics. The topic 1 has keywords such as "vehicle, howard, garage, driver, door, apartment, desk, nephew, complaint" and more, so we determined that this topic is related to traffic violations and domestic disturbances. However, topic 2 has keywords such as "fail, car, arrest, driver license, enter, refuse, unprofessional" and others, so we quickly realized that there was some overlap between the topics despite the distance map reporting that there is not.

Overall, we found that several of the topics the LDA model found had similar contextual words in them, which made it impossible to determine whether they matched up with what the reported allegation category was for a given civilian-complaint allegation report summary.

Our keyword analysis of the summaries can be seen in figure C.7 and a word graph . We used the keyBERT package to generate our keyword models. The words such as "state, fail, arrest" were found as prominent key words in most of the report summaries. However, these words do not fit into any specific allegation category again, so our keyword topics are equally as bad as our topic model.

Police Complaints

Figures C.9 and C.10 show the number of reports with summaries for each allegation category and allegation name. These reports are police reported allegations that result in police discipline of at least 1 of the reported policemen.

We used LDA to perform topic modeling. The best LDA model was chosen based on the maximum coherence value, which we found to be 8 topics. The coherence values for other groups can be found in C.11.

The intertropic distance map of our discovered topics can be found in C.12. We again found that many of the topics shared keywords such as indebtedness, inventory, and compliance. However, we achieved better overall topics that were similar to the allegation categories, as topic 1 seemed to relate the most with indebtedness, although the keyword indebtedness appeared in several topics, other words like "resolve_indebtedness" and "compliance_indebtedness" showed up in this category. Topic 4 seemed to relate to insubordination, which is a part of "personnel violations". However, none of the other categories seemed to divide evenly into the allegation categories. We saw that some allegation categories such as 'drug/alcohol abuse' were distributed in several categories, with keywords like "narcotics, substance, and alcohol" showing up in several topics(1, 3 and 5 respectively).

We also attempted to search for any keywords using keyBERT to determine whether the keywords found using that method were any different from the keywords found using the GENSIM library. However, these keywords were all similar to the ones found using GENSIM.

Future Work

We planned on using this checkpoint to verify that the data we are seeing in each allegation category is accurate. After analyzing the summaries, we determined that they contain a lot of unstructured data that provided little value when doing a topic analysis. Additionally, our keyword analysis did not provide any better results/insights. We set out to answer the question of "does a summary match up with what the reported allegation category is?", but the topics found by LDA seemed to have little semantic meaning. Further exploration of the topics of these summaries is necessary.

Additional themes in NLP that can be explored in the future:

1. One can also work on clustering of the complaint reports.
2. Though all the complaints will be negative in nature, the scale of negativity in the reports might vary. All negativity need not be the same. One can build a sentiment classification system on the scale of negativity of the complaint reports.

Conclusion

Through our different probes, we found that several factors had no effect on police discipline in civilian or officer complaint reports. However, some of our inquiries did reveal potential causal relationships behind officer disciplines.

For the first few checkpoints, we revealed some data about the differences between civilian and officer complaints — primarily, the topic of the complaint and whether officers were disciplined. However, we did not find any genuine connections when exploring this data. A large reason for this involves the lack of recent data in terms of complaint reports. For example, when viewing the bar chart race interactive visualization in checkpoint 3, you can see that the scale of the x-axis grows smaller and smaller as the years go on. Thus, it is hard to discern any associations when the more recent data is not updated.

In checkpoint 4, however, we do reveal some interesting graphs and connections that could be pertinent for future police reform. There may be some racial biases in whether an officer is disciplined and there also may exist a relevant factor when you consider that a few officers may influence others to follow in their ‘bad’ footsteps. Further analysis is present in CP4.

Lastly, we discovered that certain categories of allegations lead to discipline more often than others, and that these categories are the same whether the complaint report is filed by a civilian or an officer. Specifically, “operation/personnel violations”, “use of force”, and “conduct unbecoming” had the most number of disciplines. This is strange, because we expected more civilians to file “use of force” complaints initially. We realized that operation/personnel violations are classified loosely, and this category encompasses a wide range of offenses, from Seatbelt Violations to Property Damage. It led to us determining that a lot of the labels for allegation categories are extremely broad, and encompass a wide range of officer offenses. However, the allegation name labels are not broad enough (we did not have enough data in each allegation name to display trends among that data).

Appendix A: CP2 Figures

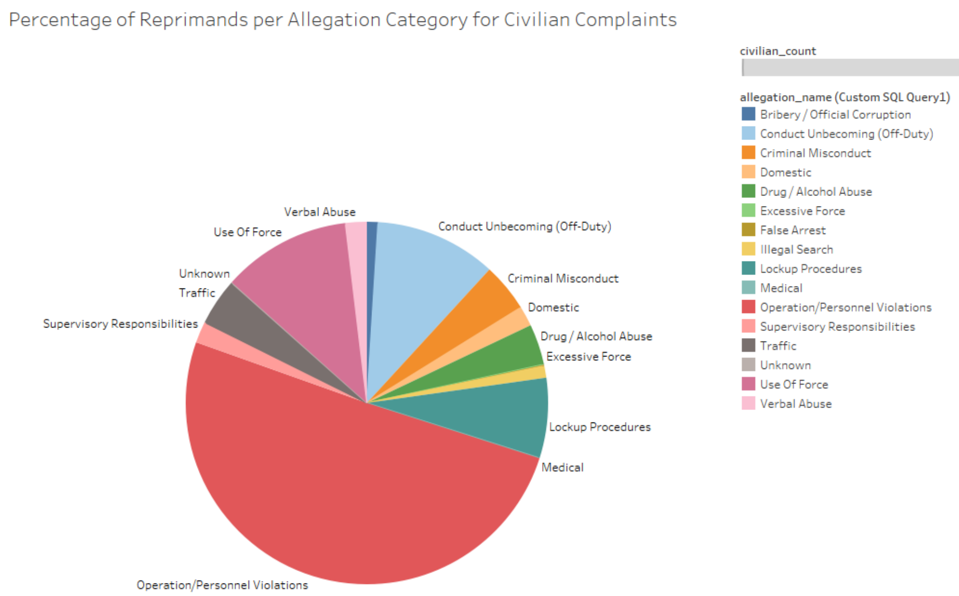

Figure A.1. Percentage of Reprimands per Allegation Category for Civilian Complaints.

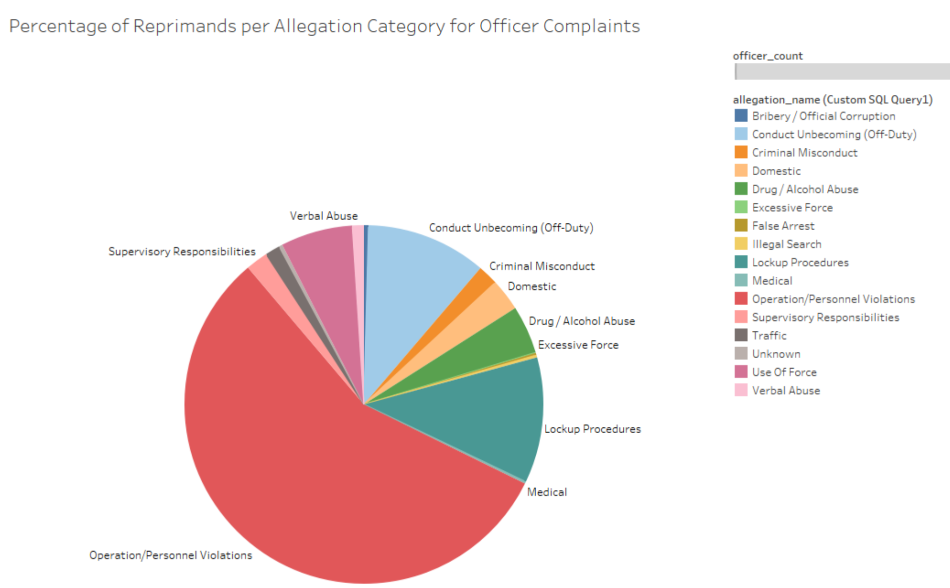

Figure A.2. Percentage of Reprimands per Allegation Category for Officer Complaints.

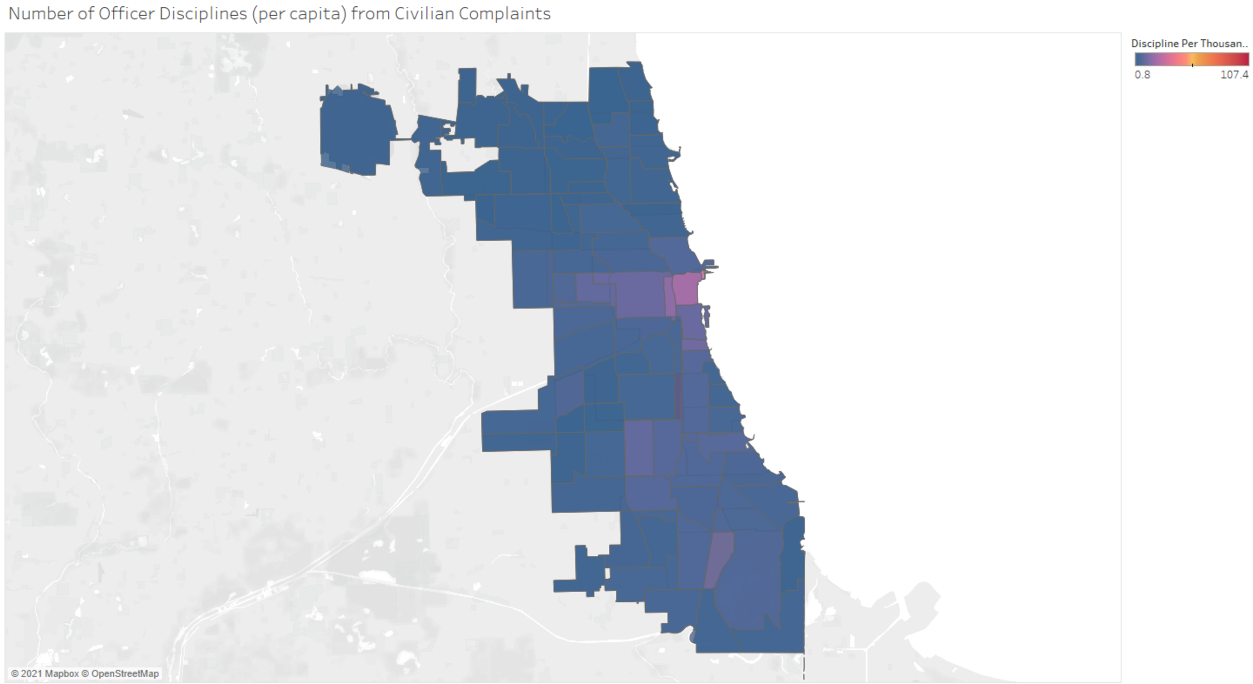

Figure A.3. Number of Officer Disciplines (per capita) from Civilian Complaints.

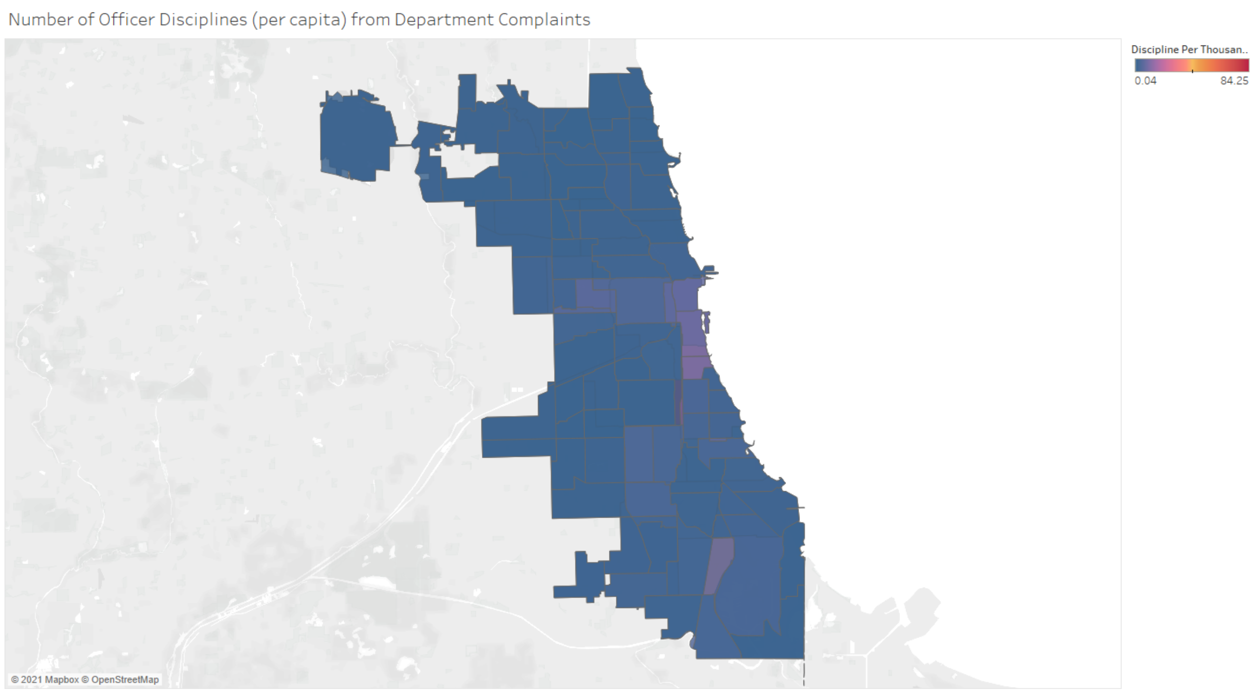

Figure A.4. Number of Officer Disciplines (per capita) from Department Complaints.

Appendix B: CP4 Figures

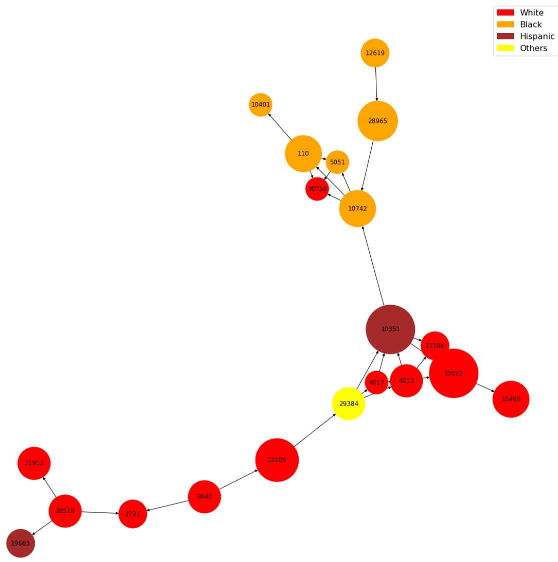

Figure B.1. Plot of a civilian complaint component.

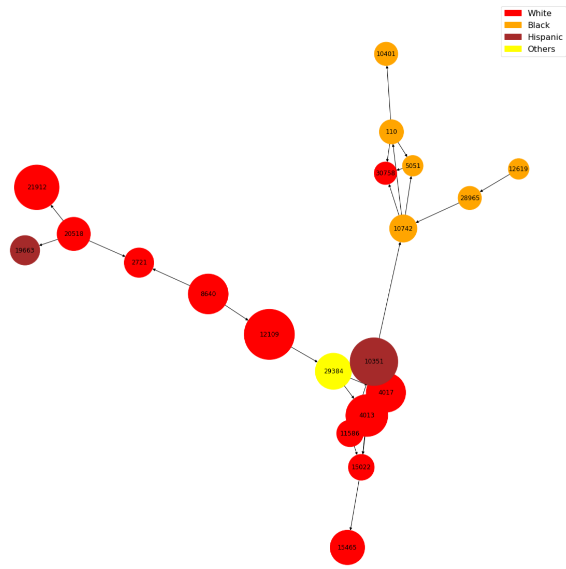

Figure B.2. Plot of Figure 1 with allegation counts.

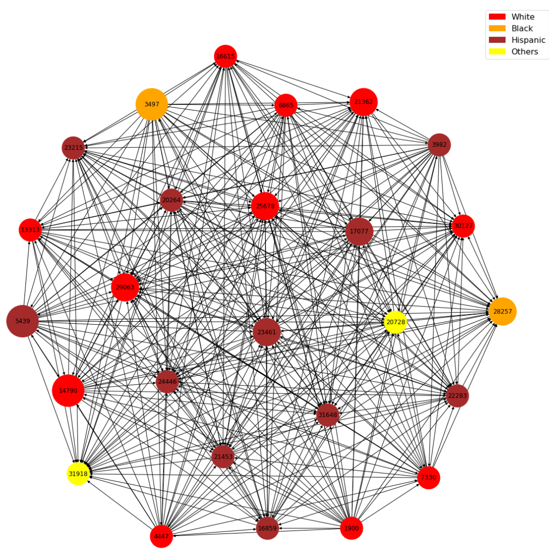

Figure B.3. Plot of a police complaint component.

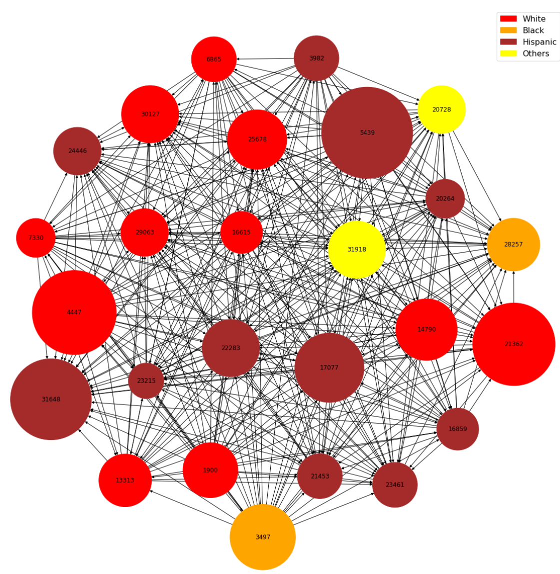

Figure B.4. Plot of Figure 3 with allegation counts.

Appendix C: CP5 Figures

```
df_civ_complaints["category"].value_counts()
```

```
Operation/Personnel Violations    25
Lockup Procedures                  5
Conduct Unbecoming (Off-Duty)      4
Illegal Search                     3
Use Of Force                       3
Traffic                            2
Criminal Misconduct                2
Domestic                           1
Drug / Alcohol Abuse               1
Supervisory Responsibilities       1
Name: category, dtype: int64
```

Figure C.1. Number of Civilian Complaints in each Allegation Category

```
df_civ_complaints["allegation_name"].value_counts()
```

```
Inadequate / Failure To Provide Service                 17
Prisoners Property                                       4
Miscellaneous                                            4
Improper Search Of Vehicle                               3
Neglect Of Duty                                          2
Slow / No Response                                       2
Association With Felon                                   2
Improper Processing / Reporting / Procedures             1
Reports                                                  1
Conspiracy To Commit A Crime                             1
Damage / Trespassing To Property                         1
Indebtedness To City                                     1
Insubordination                                          1
Intoxicated Off Duty                                     1
Fail To Obtain A Complaint Register Number               1
Excessive Force / On Duty - No Injury                    1
Altercation / Disturbance - Neighbor                     1
Leaving Assignment (District, Beat, Sector, Court)       1
Domestic Altercation - Physical Abuse                    1
Arrest, Improper Procedures                              1
Name: allegation_name, dtype: int64
```

Figure C.2. Number of Civilian Complaints in each Allegation Name

```
Number of Topics 3
Coherence Value 0.3474739616186633
Number of Topics 5
Coherence Value 0.4423622050481605
Number of Topics 8
Coherence Value 0.38698400669130695
Number of Topics 10
Coherence Value 0.3140707553355784
Number of Topics 15
Coherence Value 0.4400048883739584
```

Figure C.3. Coherence Values of Civilian Complaint Reports that Lead to officer Discipline

```
best_ldaModel_civ.show_topics()
```

```
[(0,
  '0.023*"fail" + 0.016*"case" + 0.014*"return" + 0.013*"arrest" + 0.012*"driver" + 0.012*"strike" + 0.011*"domestic" + 0.01
1*"event" + 0.011*"incident" + 0.011*"enter"'),
 (1,
  '0.032*"state" + 0.021*"complaint" + 0.017*"fail" + 0.011*"car" + 0.011*"arrest" + 0.011*"license" + 0.011*"driver" + 0.01
0*"enter" + 0.009*"refuse" + 0.008*"unprofessional"'),
 (2,
  '0.034*"refuse" + 0.020*"moe" + 0.020*"mostafa" + 0.020*"request" + 0.017*"accident" + 0.016*"car" + 0.016*"state" + 0.015
*"phone" + 0.015*"scene" + 0.015*"witness"'),
 (3,
  '0.026*"state" + 0.017*"test" + 0.017*"joke" + 0.014*"return" + 0.014*"inventory" + 0.013*"fail" + 0.010*"receive" + 0.010
*"send" + 0.010*"mail" + 0.009*"kick"'),
 (4,
  '0.033*"fail" + 0.016*"complete" + 0.014*"arrest" + 0.013*"order" + 0.013*"protection" + 0.013*"vehicle" + 0.012*"complain
t" + 0.011*"howard" + 0.011*"franklin" + 0.010*"tell"')]
```

Figure C.4. Subset of Keywords in each Topic of Civilian Complaint Reports

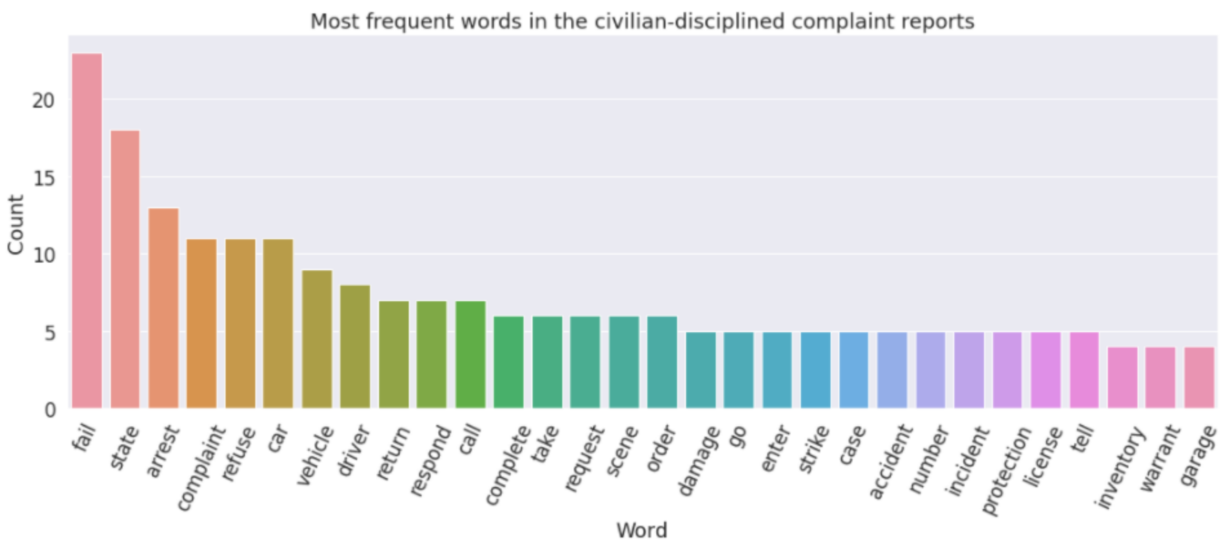

Figure C.5. Word Count Graph for Civilian Complaint Reports

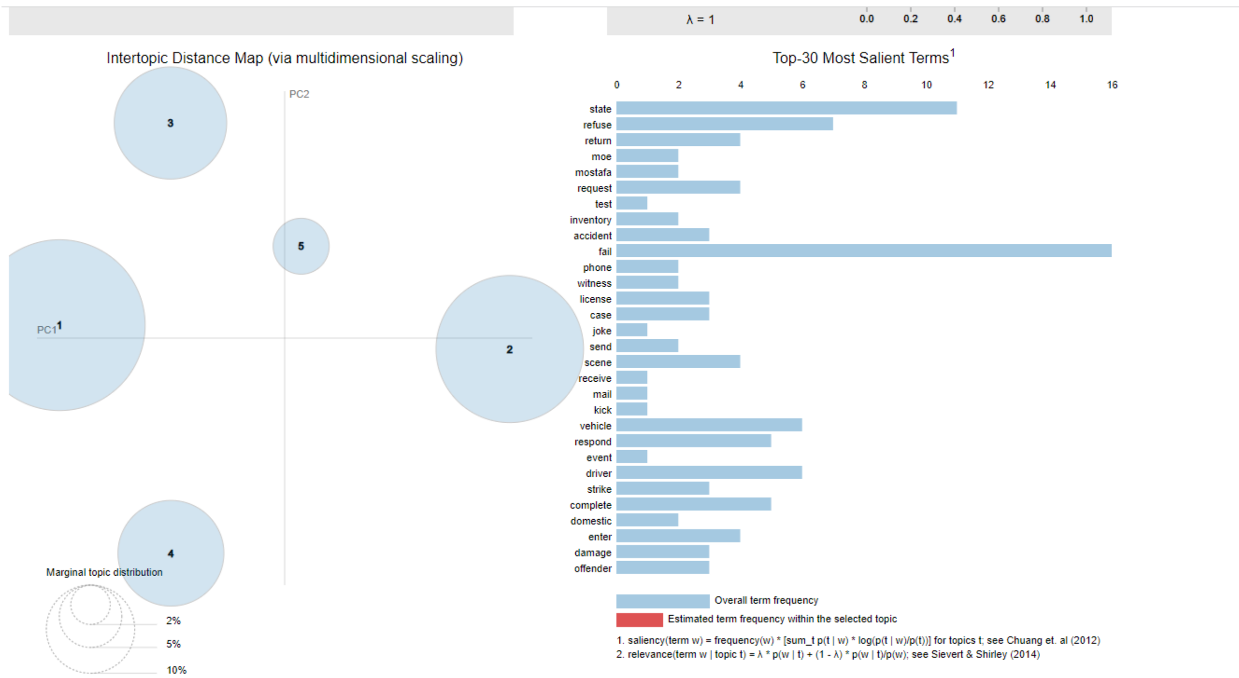

Figure C.6. Intertropic Distance Map for Civilian Complaint Reports

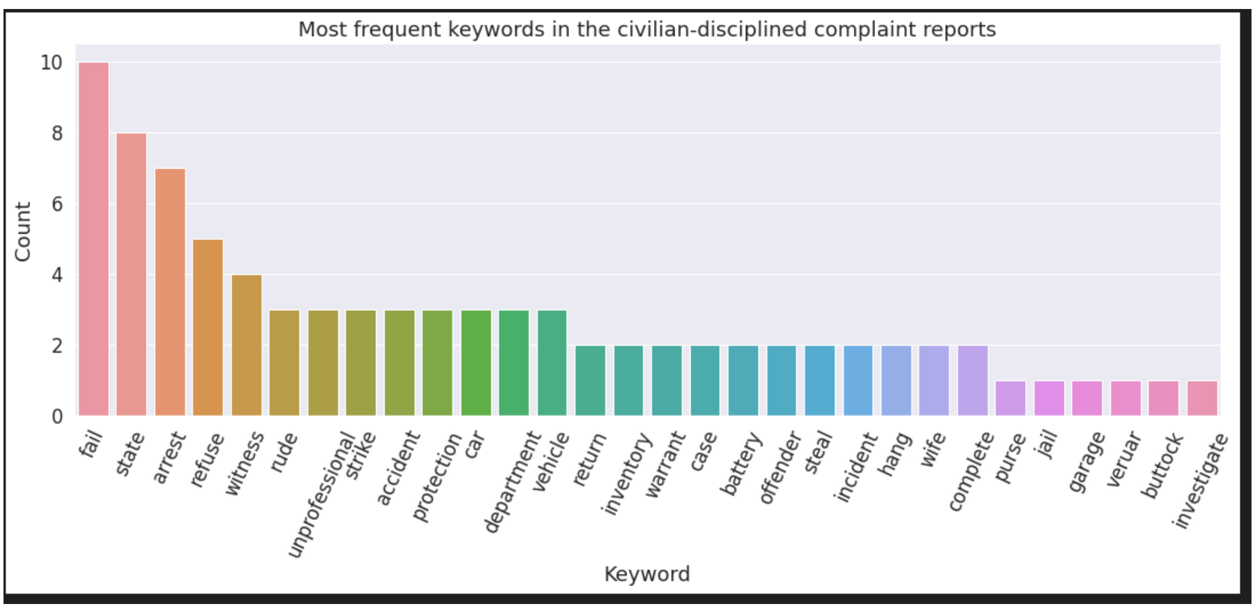

Figure C.7. Word Counts of keywords using KeyBERT for Civilian Complaint Reports

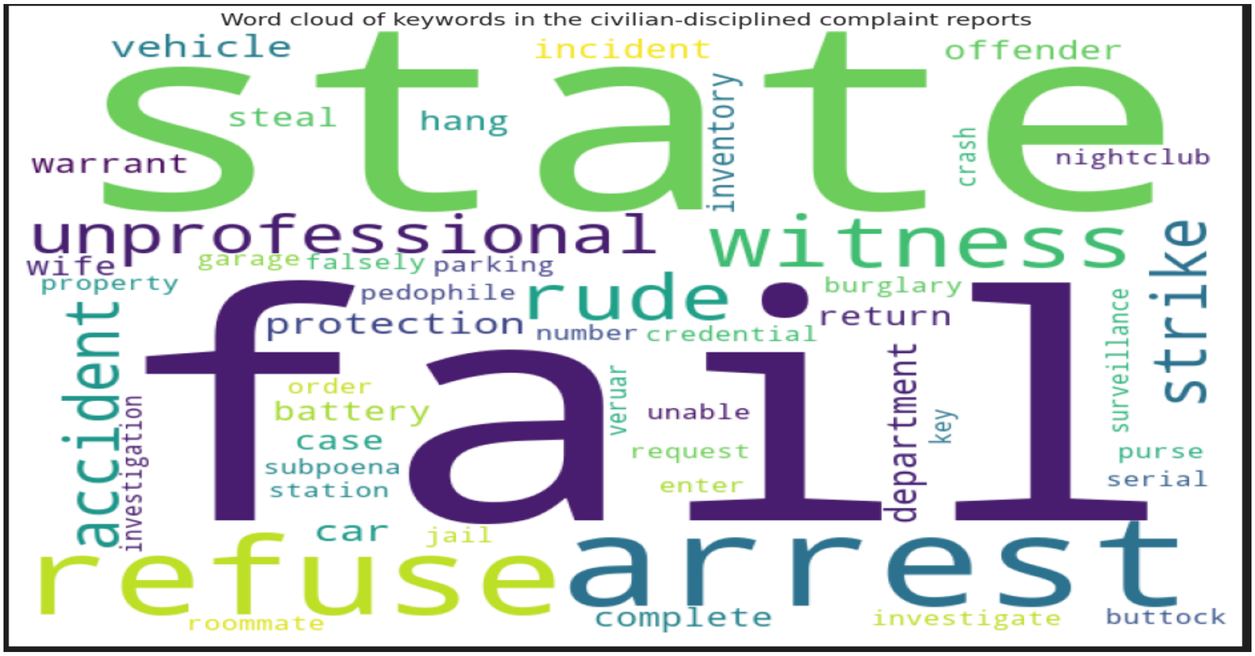

Figure C.8. Word Counts using KeyBERT for Civilian Complaint Reports

```
df_pol_complaints['category'].value_counts()

Operation/Personnel Violations    209
Conduct Unbecoming (Off-Duty)      87
Lockup Procedures                  24
Drug / Alcohol Abuse               11
Criminal Misconduct                 5
Bribery / Official Corruption       3
Use Of Force                        2
Traffic                             1
Illegal Search                      1
Supervisory Responsibilities        1
False Arrest                        1
Name: category, dtype: int64
```

Figure C.9. Number of Officer Complaints in each Allegation Category

```
df_pol_complaints['allegation_name'].value_counts()[0:25]
```

```
Neglect Of Duty                                                 77
Indebtedness To City                                            70
Miscellaneous                                                   29
Weapon / Ammunition                                             23
Insubordination                                                 22
Misuse Of Department Equipment / Supplies                       15
Association With Felon                                          13
Escape                                                          13
Inventory Procedures                                            10
Leaving Assignment (District, Beat, Sector, Court)               9
Seat Belts                                                       9
Search - Person / Property                                       4
Intoxicated On Duty                                              4
Absent Without Permission                                        4
Prisoners Property                                               4
Court Attendance Irregularities                                  3
D.U.I. - Off Duty                                                3
Gang Affiliation                                                 2
Inadequate / Failure To Provide Service                          2
Conspiracy To Commit A Crime                                     2
Secondary/Special Employment                                     2
Excessive Force - Use Of Firearm / Off Duty - No Injury          2
Reports                                                          2
Bonding/Booking/Processing                                       2
Intoxicated Off Duty                                             2
Name: allegation_name, dtype: int64
```

Figure C.10. Number of Officer Complaints in each Allegation Name

```
Number of Topics 3
Coherence Value 0.4642141918227911
Number of Topics 5
Coherence Value 0.41050223788609497
Number of Topics 8
Coherence Value 0.46513365822195474
Number of Topics 10
Coherence Value 0.44409424866042
Number of Topics 15
Coherence Value 0.4293151886679532
```

Figure C.11. Coherence Values of Officer Complaint Reports that Lead to officer Discipline

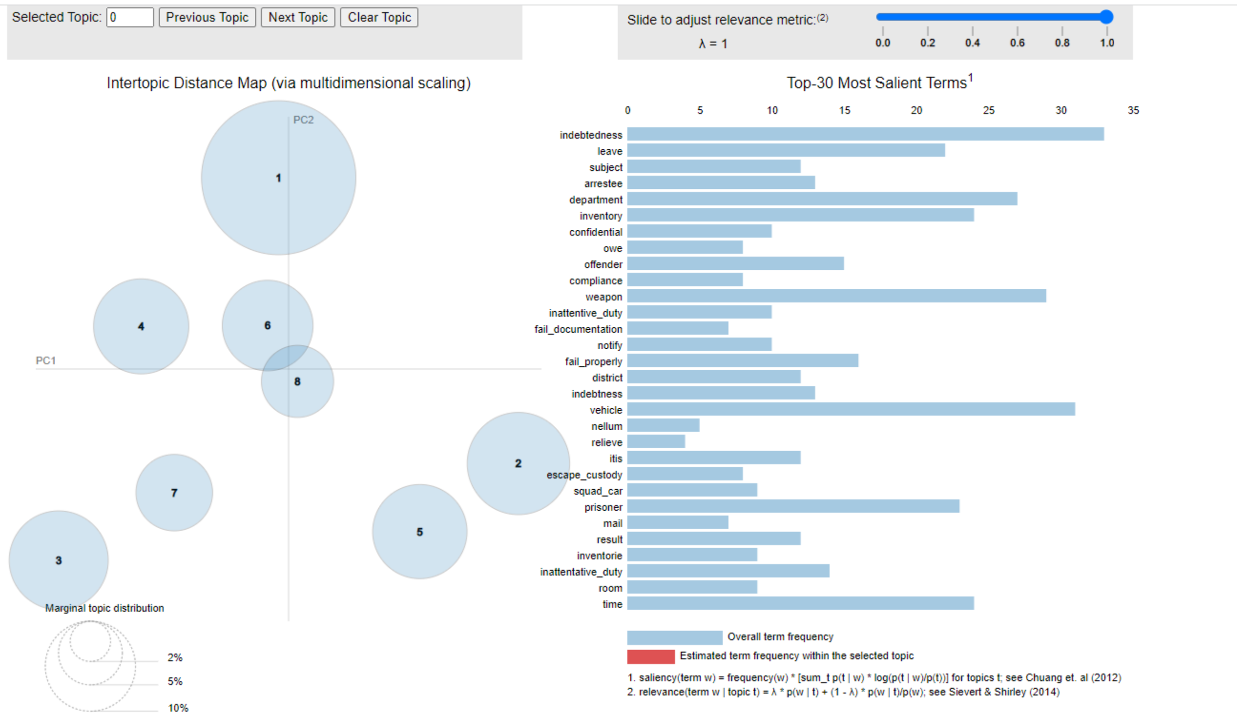

Figure C.12. Intertropic Distance Map for Officer Complaint Reports

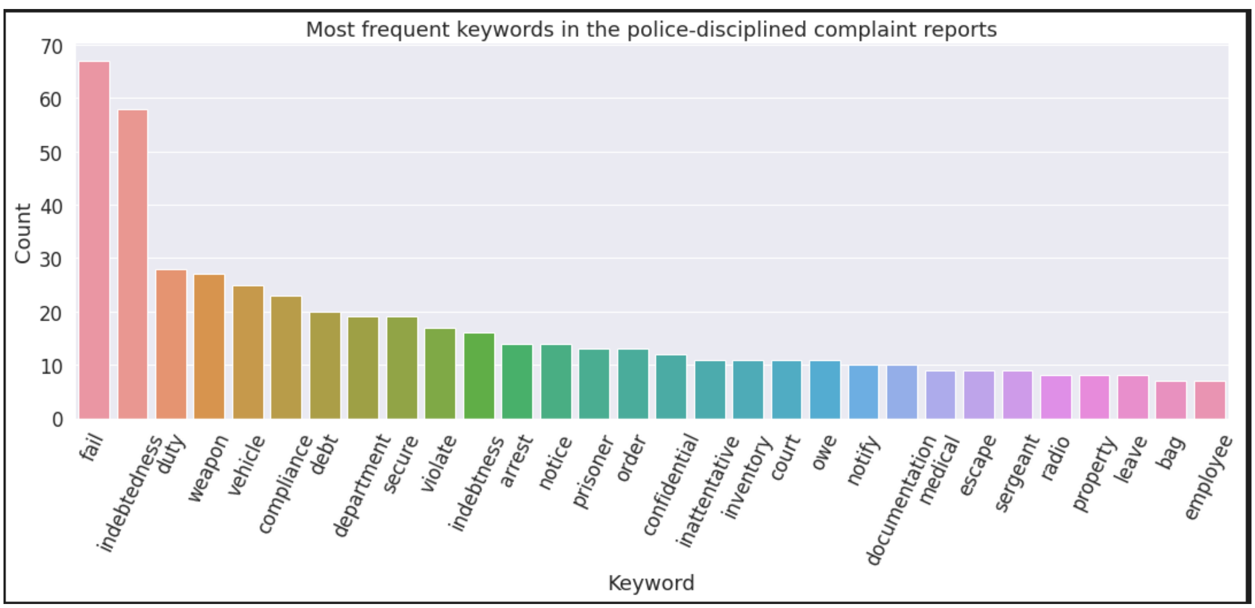

Figure C.13. Word Counts using KeyBERT for Officer Complaint Reports

Figure C.14. Word Cloud generated using KeyBERT for Officer Complaint Reports