Checkpoint 2: Data Visualization Findings

The Enchanted Badgers
Alexander Einarsson, Sergio Servantez, Marko Sterbentz
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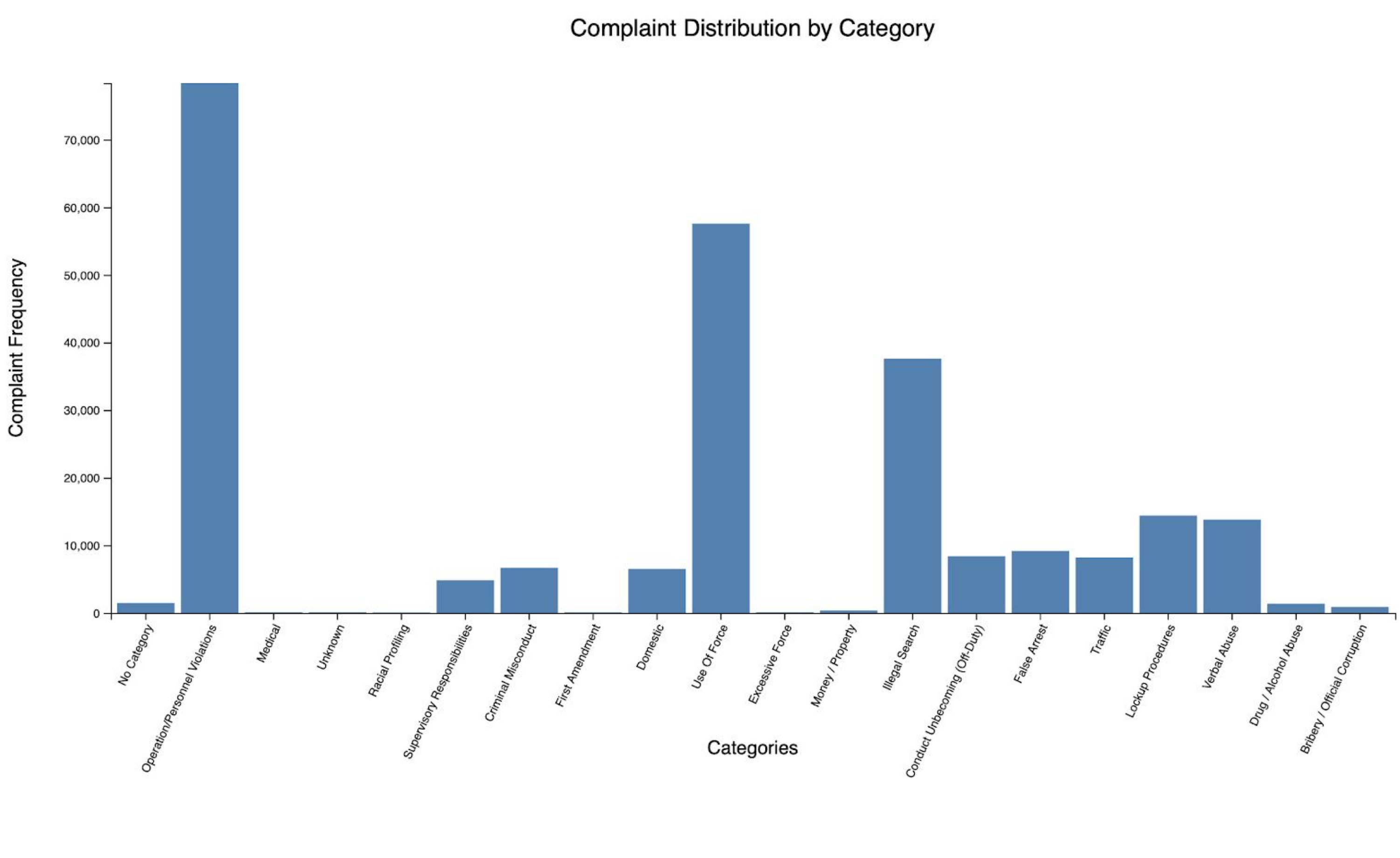
The theme of our project is to identify meaningful categories for uncategorized complaints by analyzing the relationship that exists between the complaint category and the complaint report narrative, and to use this new information to explore various aspects of complaint investigations and outcomes. To this end, we sought to answer the following set of questions by making use of the Citizens' Police Data Project database in order to produce visualizations:

1. Horizontal bar chart to visualize the distribution of complaints (before our topic modeling and after).
2. A grouped bar chart showing the classifications of uncategorized complaints using various language models.
3. Line chart to visualize the percentage of uncategorized complaints (year over year).

The visualizations and analysis are provided below. Additionally, we have provided a discussion on our use of transformer models to classify uncategorized complaints and our process for cleaning and integrating additional complaint narratives that were not already in the CPDP database in the Appendix at the end of this document.

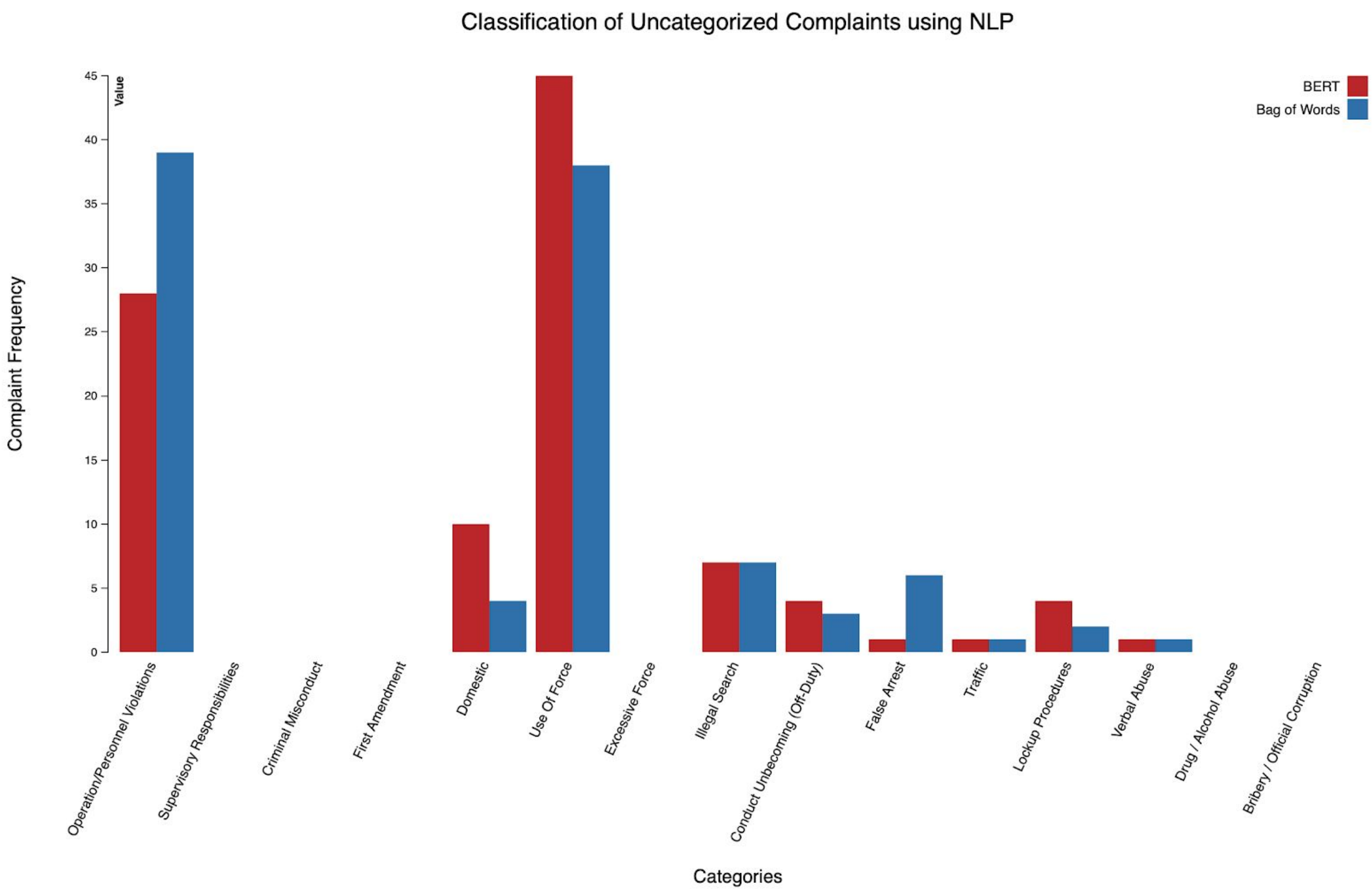
Question 1: Horizontal bar chart to visualize the distribution of complaints



The chart above shows the complaint distribution across the existing categories. We can immediately see that the distribution is far from uniform. Some categories contain almost no complaints while others contain tens of thousands. The three categories with the highest frequencies are operation/personnel violations, use of force, and illegal search (in descending order). The frequency of these categories far outnumber the others.

Surprisingly, the chart shows that there is a stark difference between the frequencies in the “use of force” category (57,574) and the “excessive force” category (31). It is not clear what the dividing line between these two categories is, or why excessive force was so rarely selected. It seems likely that this was a choice being made by the reporting officer. In our future work, we will use LDA to group complaints based on the report narratives. It will be interesting to investigate whether some of these complaints are actually more aligned with the excessive force category.

Question 2: A grouped bar chart showing the classifications of uncategorized complaints using various language models. *(originally: Stacked bar chart to visualize which category has the most miscategorized complaints, and what types of miscategorized complaints.*



We wanted to answer this question in order to determine which complaint types were most frequently miscategorized by the Chicago Police Department in order to determine if there were any types of complaints that were being miscounted by them, either intentionally or unintentionally.

We define miscategorized complaints as those complaints that are either intentionally or unintentionally provided an incorrect label. Since there is no ground truth for this data, the dataset we are working with is the set of complaints that have no category assigned to them, or were listed as Unknown in the database. We also limited our classification to those complaints that had text summaries associated with them. This latter constraint resulted in a surprisingly small number of complaints to work with, as many of the Unknown and uncategorized complaints lacked text summaries. Due to the small number of miscategorized complaints that had summaries in the database, it no longer made sense to produce a stacked bar chart as we originally intended. When we tried this, the result was a stacked bar chart in which it was immensely difficult to see the changes, and thus virtually impossible to visually compare the number of complaints in each category before and after performing the classification.

As a result, we opted to pivot from the original visualization to the following: **A grouped bar chart showing the classification of uncategorized complaints using various language models.**

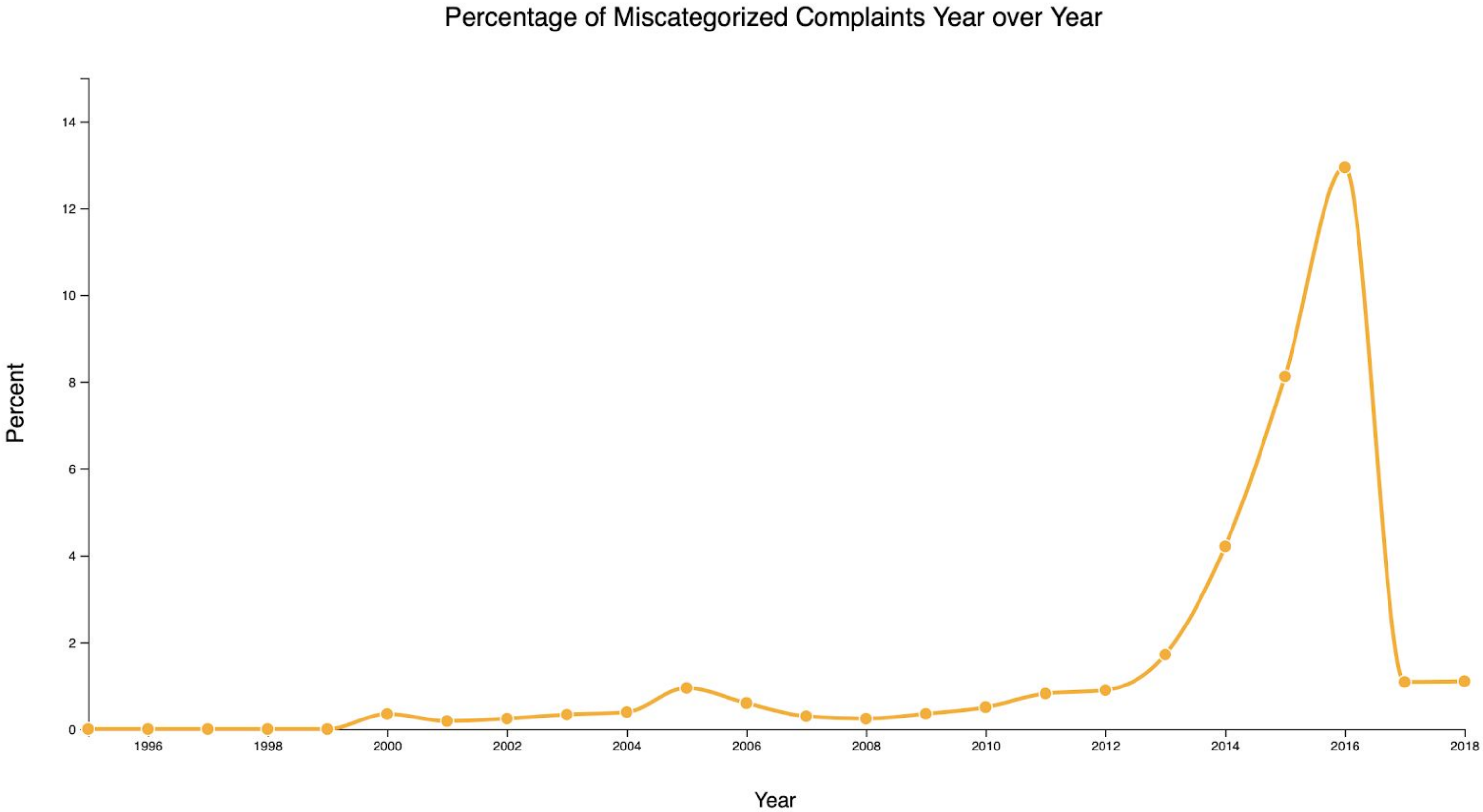
Note that in order to obtain the category for the previously uncategorized complaints, we needed to train a language model in order to classify these complaints. For the details on how this was done, please see the Appendix at the end of this document.

Looking at the resulting visualization, there are a number of interesting observations that jump out. The first is the high number of uncategorized complaints that were classified as belonging to the “Operations/Personnel Violations” category. This category seems to be a sort of catch all category, and it stands to reason that a high number of uncategorized complaints would fit into this category. This could simply be the result of the person in charge of categorizing the complaint being unsure what to report as the category, but it could also be that these typically intra-department complaints being intentionally obfuscated in order to obscure the problems occurring within the department. In order to confirm this, more qualitative analysis of these complaints will be required.

It is also quite interesting that both of the models classified a higher number of uncategorized complaints with the “Use of Force” category. Further qualitative analysis of the complaints that were classified into this category would be needed to determine whether these were intentionally miscategorized, if it was an honest mistake (i.e. multiple categories make sense), or simply a mistake by the language model classifiers. However, if it is indeed the case that these complaints were obviously miscategorized by the Chicago Police Department, this would provide compelling supporting evidence for a need to improve the reporting system citizens use to hold officers accountable. In future work, we are planning to explore the effect that a complaint’s categorization has on the final outcome of the complaint. It is possible that certain categories of complaints are treated more seriously by the department. It could also be possible that intentionally miscategorizing these complaints is an attempt to protect certain officers from further scrutiny. A definitive answer to this requires more work.

Additionally, the discrepancies in the classifications of the two models warrants further investigation. It could be the case that a single complaint viably fits into two categories, but the different model architectures are picking up on different signals in the text. This warrants further investigation as part of some future work.

Question 3: Line chart to visualize the percentage of uncategorized complaints (year over year).



The line chart shows the percentage of complaints categorized as ‘Unknown’ or that weren’t categorized at all, year over year (note that years before 2000 had zero uncategorized complaints, so we truncated the graph before 1995 for clarity). For future research of this type, it would be worthwhile to look into if anything changed in reporting practices in 2000 that led to the sudden appearance of the ‘Unknown’ category. Based on the time period, this may have been a result of the change to digital records, but that is purely hypothetical.

Starting with the year 2000, the line chart shows that the Unknown/uncategorized percentage remained relatively low (sub two percent) for just over a decade. Starting in 2013, however, we see that the percentage of Unknown/uncategorized increased rapidly, to reach a peak in 2016 at almost 14 percent, over an order of magnitude more than at any point between 2000 and 2012. After this peak, the Unknown/uncategorized complaint percentage plummets, back to almost the same level as before 2013. There seems to exist a clear explanation for why that percentage would lower drastically after 2016: the Invisible Institute gained access to the CPDP data in late 2015 and started publishing articles about the police department using this data. It can be surmised that the CPD put more pressure on their officers to correctly categorize complaints as a way to avoid bad publicity after this point. Given the value in correctly classified complaints, this increased transparency into the department via the CPDP data can only be viewed as a positive.

However, the question remains why the Unknown/uncategorized complaints so drastically increased for a few years starting in 2013. We have been unable to find any evidence that there was a drastic change in the department around this time, and we lack the insight in the goings-on in the department to come up with any testable hypotheses. We recommend that the Invisible Institute do a qualitative exploration of the reports around that time to see if there was an explosion in complaints load, if the reporting of the complaints changed, or if there are other possible explanations for the sudden increase in Unknown/uncategorized complaints. Future research projects could and should test hypotheses that the Invisible Institute can form based on such a qualitative exploration project.

Reflections on Tableau and D3

We originally intended to produce the visualizations in Tableau but ran into a myriad of issues. Most of these issues were related to accessing data from the database (both locally and AWS). Once connected to the database, one of two issues would occur after only a few minutes: 1) the connection to the database would be lost, or 2) all SQL queries to the database would fail with an error message. The only way to regain the ability to access data was to restart Tableau. We tried all the fixes mentioned on Piazza, including reinstalling many different versions of Postgres (we tried several versions of Postgres 12 alone). None of these actions worked so we pivoted to using D3. We encountered no issues using D3 and found it pleasantly easy to generate our visualizations. Overall we were underwhelmed by the Tableau platform to say the least.

Appendix: Cleaning and Integrating Additional Narratives

For Question 2, we needed to be able to classify the uncategorized narratives in the datasets provided by the Invisible Institute. In order for a language model classifier to be properly trained, there needs to be a sufficient amount of training data. Within the CPDP database, there are roughly 1100 complaints that have narrative summaries associated with them. Unfortunately, this was not enough raw data with which to train these kinds of models. When fine-tuning a BERT model on this set of complaint narratives, we were able to achieve a classification accuracy of 66.8% on the test set. This number, while better than one might expect for a multi-class classification problem such as this with so few data points, was still far lower than we would like.

Fortunately, in addition to the narrative summaries that are associated with allegations in the CPDP database, there was a set of roughly 45,400 narratives external to the database that were available. However, before being ready for usage, these summaries needed to be cleaned and integrated with the summaries and complaints already in the database.

In order to do this, we first needed to gather the data together. This included downloading the new set of narratives from The Invisible Institute's GitHub document analysis repository.

Additionally, a dump of the data_allegation table was downloaded in order to make it easier to clean and integrate these datasets using Python and Pandas.

First, this script (“narrative_cleaning_integration.py”) processes the “narratives.csv” file. We first take all rows that have a column_name of either “Initial / Intake Allegation” or “Allegation”. Then, in the result set of 31,572 rows, there are a variety of complaints that have summary text that consists entirely of either “(None entered)” or “NO AFFIDAVIT”. These are replaced with an empty string in order to match the format of the complaints already in the data_allegation table. The complaints texts also have a bunch of seemingly random carriages returns sprinkled throughout the summaries which are likely the result of the optical character recognition software. These carriages returns are replaced with spaces. We also strip white space from the front and end of the text, and then remove any rows where the summary text is an empty string. Lastly, there are duplicate summaries contained in the set, some of which are different and have varying lengths. Upon further examination of the data, it appears duplicate summaries for a single complaint would have increasing amounts of detail the longer the summary was. So, as a heuristic, we remove duplicates and keep the row that had the longest summary for that complaint. This will maximize the amount of information that the language model will have to train and perform the classification with.

Next, we had to integrate this with the data and narrative summaries from the data_allegation table. This first entailed loading the data into a Pandas data frame and dropping the unnecessary columns. This resulted in a data frame with columns of “crid” and “summary”. The columns of the new narratives were renamed to match these two columns, and the data frames were concatenated. The same duplicate removal procedure we used when cleaning the new narratives was adopted here as well, and we also make sure to remove any rows that do not have a summary. The end result is a set of narratives associated with the proper complaint report ID. There were 16010 rows of data here.

The resulting cleaned and integrated set of complaints and their narratives was written out to a CSV file called “all_narratives.csv”. In order to generate a dataset with the complaints, their summaries and other associated data, we need to create a new table in the database in order to join these summaries with the other data. To this end, we ran the following SQL table creation query:

```
CREATE TABLE data_narratives (
    id SERIAL,
    cr_id varchar(30),
    summary text,
    PRIMARY KEY (id)
);
```

Then, we loaded in the integrated narrative dataset into this table with the following SQL query:

```
COPY data_narratives(cr_id, summary)
FROM '/full/path/to/all_narratives.csv'
DELIMITER ','
CSV HEADER;
```

The '/full/path/to/all_narratives.csv' obviously needs to be replaced with the actual full path to the "all_narratives.csv" file. After this, there was a table called data_narratives that contained all narrative summaries and the id of the complaint record with which they are associated. We used the following SQL query to join this data with a couple of other tables in order to produce a full set of narrative summaries, the complaint they are associated with, the final outcome of this complaint, and the category of this complaint.

```
SELECT oa.allegation_id as allegation_id,
       oa.allegation_category_id as category_id,
       ac.category as category,
       oa.final_outcome as final_outcome,
       n.summary as summary
FROM data_officerallegation oa
    INNER JOIN data_allegationcategory ac on oa.allegation_category_id
= ac.id
    INNER JOIN data_narratives n on oa.allegation_id = n.cr_id
WHERE n.summary > '';
```

The results of this query were then downloaded into a JSON file that is used as input into the final data processor that prepares the data for use in training the language models.

Using Language Models to Classify Uncategorized Complaints

The data processing script ("process_raw_data.py") reads this JSON file into a Pandas data frame. We first count the number of complaints associated with each category. The class and data distribution is as follows:

Category Label	Number of Complaints
Bribery / Official Corruption	41
Conduct Unbecoming (Off-Duty)	292
Criminal Misconduct	42

Domestic	283
Drug / Alcohol Abuse	52
Excessive Force	11
False Arrest	1373
First Amendment	5
Illegal Search	2330
Lockup Procedures	966
Operation/Personnel Violations	4166
Racial Profiling	3
Supervisory Responsibilities	89
Traffic	280
Use Of Force	1575
Verbal Abuse	144

Any category that has less than 5 training samples associated with it lumped into a category called “other_category”. We do this since any category with less than 5 training samples likely does not have enough training data to properly classify narratives as coming from this category.

We then make use of Scikit-Learn’s train_test_split() function to divide the resulting set of samples into training, validation, and testing data sets with a train/validation/test split of 60/20/20. We then create three TSV files containing the set of samples and their class/category for each of the training, validation, and testing data sets.

With the final training and testing datasets put together, we can finally train the language model classifiers. For this task, we trained two models: a bag of embeddings models and a BERT transformer model. The bag of embeddings model is similar to a bag of words model except we use word embeddings rather than raw words or n-grams.

The training process makes use of the AllenNLP framework, which provides a wrapper around a variety of transformer implementations, including the BERT model. The BERT model has already been pretrained on a massive corpus of text, and all we need to do now is add a classification output layer and fine-tune it on the set of complaint narratives and their classes. The code for this is included in the src directory of our submission, as are the instructions for training and testing the model.

The result is a bag of embeddings classifier which achieves a classification accuracy of 83.2% on the test datasets, and a trained BERT classifier that achieves an accuracy of 83.9%. This is far better than the 63.6% and 66.8% classification accuracies achieved by the bag of embeddings and BERT classifiers respectively when trained on the original dataset derived from the roughly 1100 complaints narratives contained in the CPDP database.

With these two classifiers in hand, it is now possible to use these models to classify the complaints in the database that have no known category. This would be the complaints where either the category is “Unknown” or is NULL and where the complaint has a summary. These complaints were retrieved from the database using the following SQL query:

```
SELECT DISTINCT oa.allegation_id as allegation_id,
       oa.allegation_category_id as category_id,
       ac.category as category,
       oa.final_outcome as final_outcome,
       c.summary as summary
FROM data_officerallegation oa
    LEFT JOIN data_allegationcategory ac on oa.allegation_category_id =
ac.id
    LEFT JOIN data_narratives c on oa.allegation_id = c.cr_id
WHERE (ac.category = 'Unknown' OR ac.category IS NULL)
  AND c.summary > '';
```

The result was 101 distinct complaints and their narratives. Using the “classify_uncategorized_complaints.py” script, we used the two models to classify these 101 complaints. The results are described in the tables below.

BERT Classification Results

Category Label	Number of Complaints
Operation/Personnel Violations	28
Illegal Search	7
Use Of Force	45
False Arrest	1
Lockup Procedures	4
Conduct Unbecoming (Off-Duty)	4

Domestic	10
Traffic	1
Verbal Abuse	1
Supervisory Responsibilities	0
Drug / Alcohol Abuse	0
Criminal Misconduct	0
Bribery / Official Corruption	0
Excessive Force	0
First Amendment	0
other_category	0

Bag of Embeddings Classification Results

Category Label	**Number of Complaints**
Operation/Personnel Violations	39
Illegal Search	7
Use Of Force	38
False Arrest	6
Lockup Procedures	2
Conduct Unbecoming (Off-Duty)	3
Domestic	4
Traffic	1
Verbal Abuse	1
Supervisory Responsibilities	0
Drug / Alcohol Abuse	0
Criminal Misconduct	0
Bribery / Official Corruption	0

Excessive Force	0
First Amendment	0
other_category	0

The results were further explored above in Question 2. We leave a more detailed exploration and analysis of these summaries for Checkpoint 5.