Final Report:
Utilizing natural language processing to derive insight from CDP Questionnaires.
By Matt Gargiulo

Problem Statement:

CDP, formerly known as Carbon Disclosure Project, provides the premier framework for both cities and corporations to disclose environmental and social data, metrics, targets, and initiatives. CDP held a competition two years ago on Kaggle to answer the question "How can companies and cities work together to better assist the most vulnerable of populations". I will provide further analysis on these data with the hope to answer the question: "Can the answers provided by each respondee provide context to where they are located"? Put another way, can I predict which city each answer is coming from based on how they answered the questionnaire? I will incorporate data science techniques such as natural language processing through spaCy, dimensional reduction through primary component analysis and isometric mapping, and clustering through KMeans.

Data Wrangling:

CDP provided data from both corporations and cities from 2018, 2019, 2020. Each data comes with a 'disclosures' file that contains information about the city or company, and a 'responses' file that contains responses to the questionnaire. The data contains over 6,700 respondents that span nearly 100 countries and numerous languages.

Additionally, questionnaire questions may contain sub-questions in the form of a table. In the screenshot below, Question 2.3a is composed of seven sub-questions.

2.3a Please report on how climate change impacts health outcomes and health services in your city.

Question Dependencies
This question only appears if you select "Yes" in response to 2.3.

Change from 2019
New question

Response Option
Please complete the following table. You are able to add rows by using the "Add Row" button at the bottom of the table.

Area affected by climate change	Health-related risk and vulnerability assessment undertaken	Identify the climate hazards most significantly impacting the selected area	Identify the climate-related health issues faced by your city	Timescale of climate-related issues for the selected health area	Please identify which vulnerable populations are affected by these climate related impacts	Please explain
Select all that apply: • Health outcomes • Health systems (service provision, infrastructure and technologies) • Areas outside the health sector (e.g. agriculture, water and sanitation, transport, power generation, built environment)	Select from: • Yes • No	Select all that apply: Appendix E	Select all that apply: • Heat-related illnesses • Vector-borne infectious diseases (e.g. malaria, dengue, Lyme disease, tick-borne encephalitis) • Water-borne and food-borne infectious diseases (e.g. diarrheal diseases and wound infections) • Air-pollution related illnesses • Exacerbation of Non-Communicable Disease Symptoms (e.g. respiratory disease, cardiovascular disease, renal disease) • Mental health impacts • Direct physical injuries and deaths due to extreme weather events • Food & Nutrition Security • Disruption to water, sanitation and wastewater services • Disruption to health service provision • Overwhelming of health service provision due to increased demand • Lack of climate-informed surveillance, preparedness, early warning and response • Damage/destruction to health infrastructure and technology • Disruption of health-related services (e.g. roads, electricity, communications, emergency/ambulatory response, laboratories, pharmacies) • Other, please specify	Select from: • Current • Short-term (by 2025) • Medium-term (2026-2050) • Long-term (after 2050)	Select all that apply: • Women • Children and youth • Elderly • Indigenous populations • Marginalized groups • Outdoor workers • Factory workers • Persons with disabilities • Persons with pre-existing medical conditions • Low-income households • Unemployed persons • Persons living in sub-standard housing • Other, please specify	Text field

Due to these nuances, the responses dataframe broke each question into a question number(Q_Num), column number (Col_Num) and row number (Row_Num) as seen below.

	Question_ID	Year	Parent_Sect	Sect	Q_Num	Q_Name	Col_Num	Col_Name	Row_Num	Row_Name
16032	16032	2018	Hazards and Adaptation	Adaptation	3.0	Has the Mayor or local government committed to...	0	NaN	0	NaN
16033	16033	2018	Hazards and Adaptation	Adaptation	3.0a	Please select the type of commitment and attac...	1	Type of commitment and attach commitment document	0	NaN
16034	16034	2018	Hazards and Adaptation	Adaptation	3.0a	Please select the type of commitment and attac...	1	Type of commitment and attach commitment document	1	NaN
16035	16035	2018	Hazards and Adaptation	Adaptation	3.0a	Please select the type of commitment and attac...	1	Type of commitment and attach commitment document	2	NaN
16036	16036	2018	Hazards and Adaptation	Adaptation	3.0a	Please select the type of commitment and attac...	1	Type of commitment and attach commitment document	3	NaN

Furthermore, certain questions have the option to “select all that apply”; the screenshot below shows an example of this. Within the ‘Climate Hazards’ sector, question 2.2a column number 9, row number 1, exists three different, unique answers. In order to combat duplicate issues further in the analysis. I combined these instances into a single row.

	Year	Account_Num	Parent_Sect	Sect	Q_Num	Q_Name	Col_Num	Col_Name	Row_Num	Row_Name	Answer
62	2018	1093	Climate Hazards	Climate Hazards	2.2a	Please list the most significant climate hazar...	9	Top three assets/ services affected	1	NaN	Emergency management
241	2018	1093	Climate Hazards	Climate Hazards	2.2a	Please list the most significant climate hazar...	9	Top three assets/ services affected	1	NaN	Food & agriculture
747	2018	1093	Climate Hazards	Climate Hazards	2.2a	Please list the most significant climate hazar...	9	Top three assets/ services affected	1	NaN	Water supply & sanitation

Turns into:

	Year	Account_Num	Parent_Sect	Sect	Q_Num	Col_Num	Row_Num	Answer
104	2018	1093	Climate Hazards	Climate Hazards	2.2a	9	1	Emergency management, Food & agriculture, Wate...

As an initial MVP model, I’ll subset the data to 5000 samples of 2020 data from cities within the United States. This way I can increase performance for later analysis and language translations won’t inhibit progress.

Finally, the original dataset organizes questions and answers into unique sectors. Originally, the dataset contained 51 of these unique sectors, which decreased to 25 following the MVP subsetting. Examples of sectors include ‘Climate Hazards’, ‘Data Management’, and ‘Water Supply Management.

Data Organization:
I will transform the two datasets into three dataframes to mimic a common practice in database warehousing known as Star Scheme. The Star Scheme approach is based around a fact table that contains all the critical information, and supporting dimensional tables which aid in filtering and subsetting of the data. Question Info (denoted in the notebooks as dim_qq_df) is a dimensional table that contains info on each question. Respondent Info (denoted in the notebooks as dim_cd_df) is a dimensional table that contains info on each respondee. Lastly, the main database (denoted fact_df) consists of the unique ids of the previous tables and the answers that I'll be conducting analysis on.

Question Info
Question_ID
Year
Parent_Sect
Sect
Q_Num
Q_Name
Col_Num
Col_Name
Row_Num
Row_Name

Main Database
Year
Account_Num
Question_ID
Answer

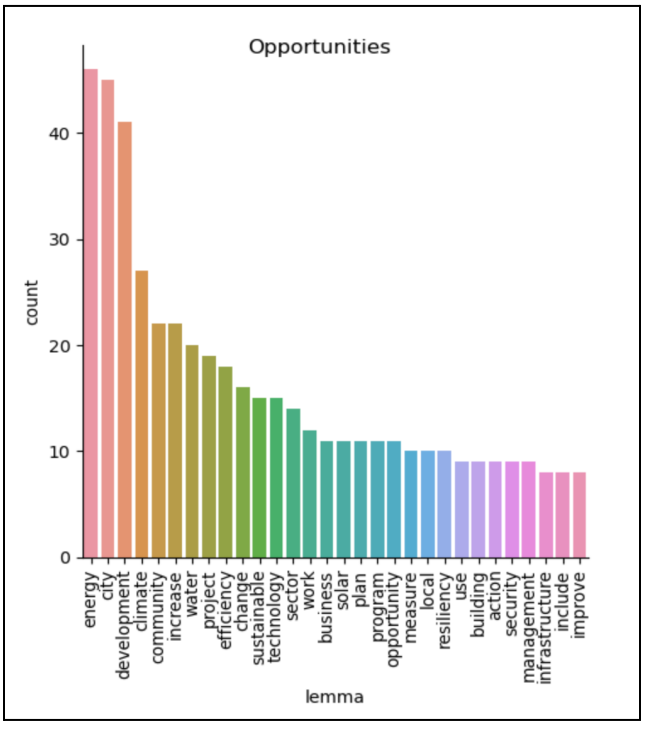
Respondent Info
Account_Num
Reporting_Year
Org
City
Country
CDP_Reg
Reporting_Auth
Access
First_Time_Disc
Pop
Pop_Year
geometry
Last_Update

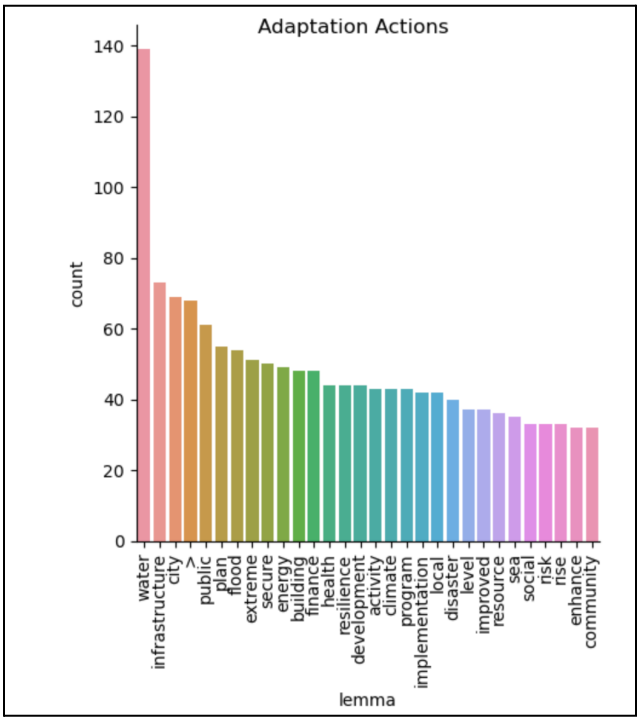
Colored columns are the keys used to match the tables.

Exploratory Data Analysis
Exploratory Data Analysis (EDA) was conducted to help understand which cities participated in the questionnaire and if there were correlations between sectors of the questionnaire and particular words.

Distribution of cities:
The dataset is well distributed across the United States. There is, however, an observable lack of data points from the northern part of the central time zone.

Distribution of words per Sector:
spaCy libraries were used to analyze the answers given to each question in the dataset. By removing punctuation, stopwords, and incorporating lemmatization, I was able to pull out the words most frequently used in each section of the questionnaire. As seen in the figures below, the 'Opportunities' sector had higher counts of words such as energy, city, development, and climate, while 'Adaptation Actions' had almost 140 different counts of the word water, nearly double of the most common word, infrastructure.



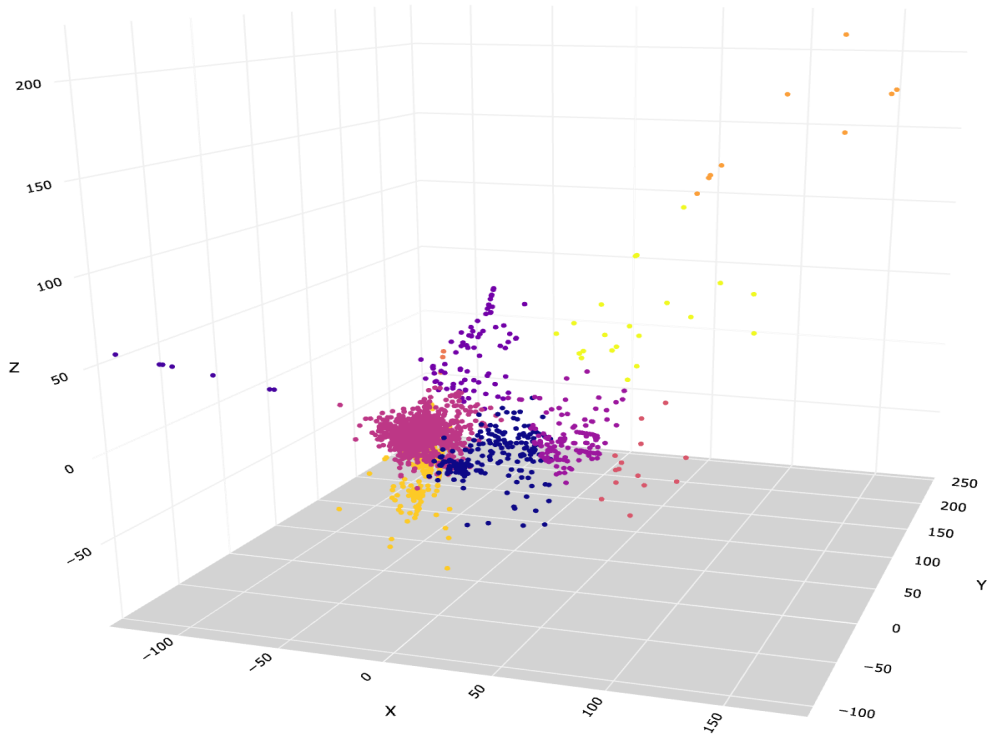


Feature Engineering and Natural Language Processing:
While the above analysis is great for initial exploration, text data needs to be analyzed in relation to their larger context. SpaCy provides word embedding to help achieve this. By utilizing neural networks, spaCy is able to take a sentence and turn it into a vector 300 features long. As an example:

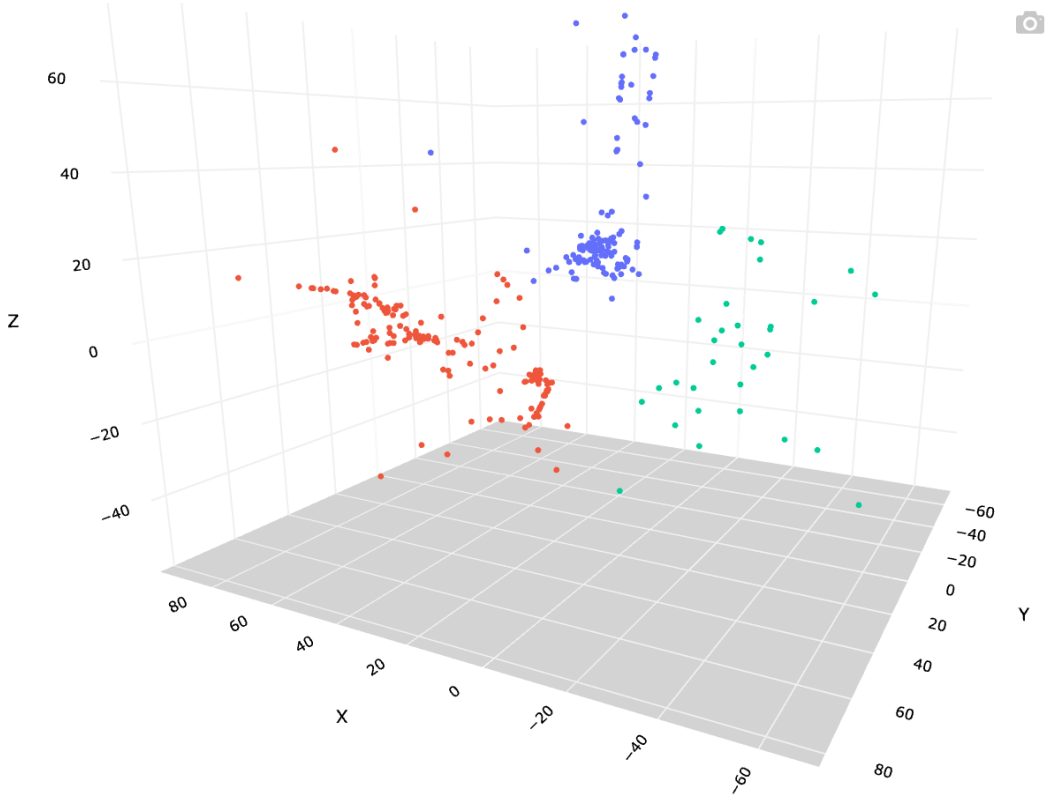
'Hello how are you doing today' translates to

```
 1.08723330e+00,  9.06183302e-01, -3.83679986e+00, -2.40873337e+00,
-1.72351170e+00,  1.32886171e+00, -3.40423375e-01,  2.91442180e+00,
-3.32732320e+00,  2.39499497e+00,  5.30920029e+00,  1.75119007e+00,
-4.65546656e+00,  2.87874937e-01,  3.80471635e+00, -1.96743155e+00,
 2.72323489e+00, -2.25011849e+00, -1.73085344e+00, -1.27153826e+00,
 1.14123333e+00, -9.70268309e-01, -1.18494165e+00, -5.62111664e+00,
-1.68206990e+00, -1.95776716e-01, -9.11533237e-02, -4.59500164e-01,
-1.43351173e+00, -4.80982848e-02,  2.32660007e+00, -1.91114330e+00,
-2.07323670e+00, -2.32495499e+00,  2.66104674e+00, -2.84925073e-01,
-7.21693337e-01,  5.99923313e-01,  4.84731817e+00,  2.49761868e+00,
 4.03339982e-01,  3.87071681e+00,  6.60196722e-01, -1.30290329e+00,
-1.98006487e+00,  1.99098158e+00,  2.97578335e-01, -5.99172974e+00,
-3.34860653e-01,  2.20990324e+00,  5.06963313e-01,  1.40931845e+00,
 2.36307359e+00, -6.88460016e+00, -3.67465472e+00, -7.53920019e-01,
-1.60733509e+00,  3.74086666e+00, -7.78914928e-01, -5.35558403e-01,
 5.99273348e+00,  2.10318351e+00,  9.71731663e-01, -2.33598495e+00,
 1.86854526e-01,  2.77317500e+00, -4.25660324e+00, -5.63235044e+00,
-2.09123850e+00,  3.34972835e+00, -1.28238666e+00,  4.19278383e-01,
-6.81999981e-01, -1.60243988e+00, -6.34551704e-01,  8.96138370e-01,
-2.60806966e+00, -2.41848528e-01, -2.11807656e+00, -1.56385994e+00,
-1.55961168e+00, -1.38044758e-02,  2.07214999e+00,  1.18699992e+00,
 2.53673530e+00,  3.91300172e-01, -7.14661598e-01, -3.17639351e+00,
 1.57173836e+00,  4.72984940e-01, -2.79213339e-01,  1.09995663e+00,
-1.57404944e-01, -5.06923342e+00, -1.67288828e+00, -9.78763282e-01,
 7.22100019e-01, -2.91381001e+00,  3.87941599e-01, -6.45343304e-01,
 3.03582001e+00,  1.19355667e+00,  2.73949981e-01, -1.19662666e+00,
-2.54734349e+00,  2.51034999e+00, -2.73521686e+00,  4.34646696e-01,
-9.35466290e-02,  4.25276548e-01,  1.96916664e+00, -3.76946640e+00,
 9.77524579e-01, -2.65504575e+00, -1.35200596e+00,  4.61793327e+00,
-2.81490016e+00, -2.48836684e+00,  2.20180988e+00, -1.16810000e+00,
-3.89171982e+00,  1.46919823e+00, -4.18907309e+00,  1.29420662e+00,
 3.34380239e-01, -3.16608357e+00,  1.55891168e+00, -2.42625165e+00,
 6.68850005e-01, -3.79269987e-01, -6.16866648e-01, -3.95440251e-01,
-7.38666058e-02, -1.66486657e+00, -3.17334128e-03,  1.12158835e+00,
-2.59439516e+00, -8.09866786e-02,  5.62633324e+00,  1.22191660e-01,
-4.02553350e-01, -1.58651495e+00,  1.28140175e+00,  1.00037336e+00,
-8.32933366e-01, -1.40311110e+00, -3.31883502e+00, -1.04473507e+00,
-1.05361164e+00, -7.61009991e-01,  6.85567409e-02,  2.63078451e+00,
 1.19653367e-01, -5.74784994e-01, -2.42200002e-01, -9.80881691e-01,
 4.05634832e+00,  8.12087297e-01, -3.23060006e-01, -2.89696860e+00,
-5.24568319e-01, -1.00069666e+00, -3.97742367e+00, -2.59822774e+00,
-3.18343520e+00, -7.27835000e-01, -3.06979847e+00,  8.30678403e-01,
```

Word embedding is extremely important because machine learning techniques such as clustering can be applied once texts are in numerical format. The figure below shows word embeddings for every answer in our dataset in 3-dimensional space.



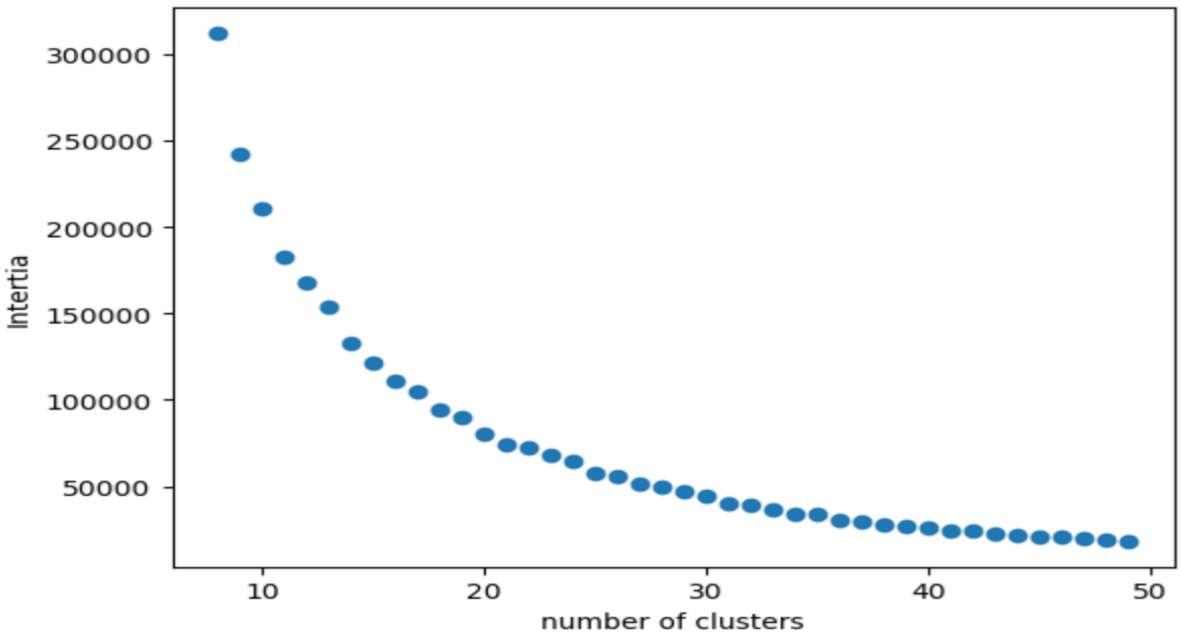
While interesting, this scatterplot does not separate the data by individual sectors. Additional analysis reveals that clustering the data by sector can lead to visualizations such as the ones below that is isolated for ‘Climate Hazards’.



Kmeans Models:
These 3D visuals utilize Kmeans clustering models, requiring that I provide the number of clusters expected to see within the data. The image above splits the data into three distinct clusters because I choose a hyperparameter value of 3. Tools such as elbow plots or silhouette analysis can help determine the ideal number of clusters.

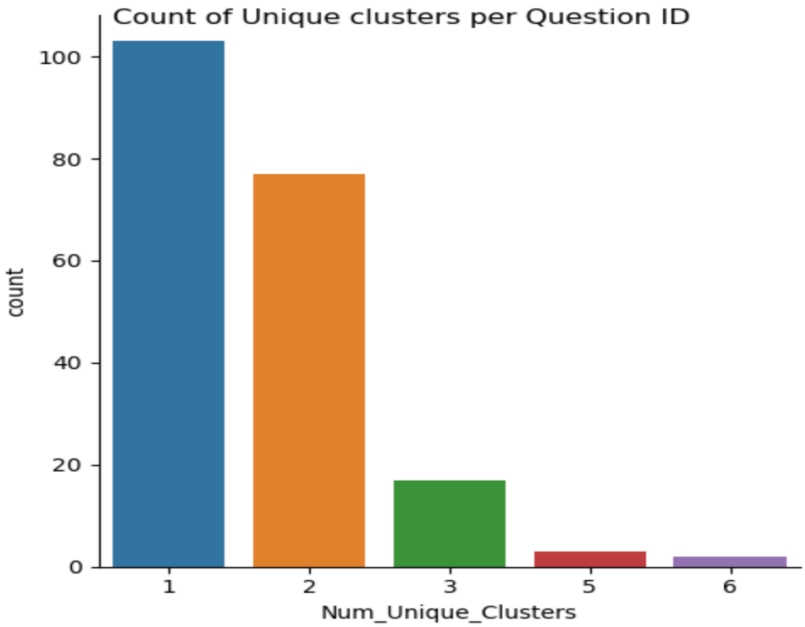
Further Clustering Analysis:
What is causing this clustering? Was the clustering caused by cities in different parts of the country preferencing certain words over others? Did the nature of each question within each sector lead to clustering?

These questions were answered by subsetting further into unique rows of sectors and questions. Again, I subsetted the data on the sector of ‘Climate Hazard’ and set the KMeans hyperparameter to 20 clusters as identified with the elbow plot below.



‘Climate Hazards’ contains 202 unique questions so being able to put the data into 20 clusters does support the notion of uniqueness with how questions are answered.

Once again focused on the ‘Climate Hazards’ sub-sector, distinct clusters are represented in 3-dimension space which diminishes the likelihood we could determine the location of the questionnaire respondee by analyzing their answers. This particular sub-sector contains 202 unique questions, of which can be grouped into 20 clusters. However, As seen by the figure below, roughly 180 of the question IDs only had 1 or 2 clusters signifying most of the answers were highly similar to one another.



Model Creation:

I concluded the analysis by constructing a model to predict city location based on answers.A random forest and KNearestNeighbors model were selected due to performance and were evaluated on f1 scores.

Both of these models returned low scores. The random forest model, however, was the better of the two with a f1 score of roughly 11 percent. The table below is a sample of the evaluation report card that shows how well the model predicted each city.

	precision	recall	f1-score	support
Abington	0.05	0.09	0.06	11
Alameda	0.00	0.00	0.00	6
Alton	0.00	0.00	0.00	1
Anchorage	0.00	0.00	0.00	11
Ann Arbor	0.23	0.24	0.23	21
Arlington	0.00	0.00	0.00	14
Asheville	0.00	0.00	0.00	18
Aspen	0.31	0.22	0.26	18
Aurora	0.00	0.00	0.00	2
Austin	0.00	0.00	0.00	11
Baltimore	0.00	0.00	0.00	20
Blacksburg	0.00	0.00	0.00	7
Bloomington	0.32	0.28	0.30	25
Boston	0.19	0.18	0.18	28
Boulder	0.25	0.26	0.26	23
Boulder County	0.11	0.17	0.13	6
Boynton Beach	0.15	0.08	0.11	25
Breckenridge	0.14	0.17	0.15	6
Broward	0.33	0.22	0.27	9
Buffalo, NY	0.29	0.25	0.27	8

Conclusion and Next Steps:

As an MVP, this report does a great job at analyzing the data and creating a basic model to predict city location based on answers to a questionnaire. However, there is a lot of room for improvement.

Next Steps:

Next steps would be to group the cities into larger sections whether that is by state or geo-regions. Unfortunately the dataset did not have states associated with the data and while we may assume, for example, that the City of Austin is referring to Austin, Texas, there is an Austin in seven different states that are represented in the dataset. I'd also

like to apply this model to every city in the dataset which would require a translation library such as google translate; and lastly, I'd like to implement the other half of the dataset which are corporate answers to a separate questionnaire.