

Assignment 4 Writeup

Abstract and Introduction (2%):

While drafting ideas for this project and the presentation for assignment 3, my first thought went to datasets involving COVID-19. Since the pandemic began back in 2020, the subject has been of great interest to me due to the fact that despite there being many studies on the topic and time period, people still disagree on COVID-19 and its effects on people and greater society. Back home, it felt as though almost no one believed that COVID-19 was nearly as dangerous as the news claimed. Since I had never met anyone who suffered extreme symptoms or death due to COVID-19, I believed this to be true as well. However, after coming to RPI, I found that the answer was not as straightforward as I once thought. Regardless, the one thing that has been clear to me since the beginning is that the pandemic caused widespread panic and isolation through the subsequent quarantine policies put in place. This led me to my hypothesis: U.S. states with higher COVID-19 mortality rates in a given week saw an increase in mental health care. Additionally, severity of mental health care can be predicted based on the local COVID-19 mortality rate.

Data Description and preliminary analysis (3%)

To prove this hypothesis, I turned to the place I thought best to find data and other statistics about COVID-19 and other diseases, the Center for Disease Control (CDC). After scouring the CDC website for suitable datasets, I stumbled upon the COVID-19 dataset (Provisional Covid-19 Death Counts by Week Ending Date and State). This dataset was key for my research as it separated COVID-19 deaths from those caused by other respiratory diseases, such as Influenza and Pneumonia. Additionally, it separated this information down to the week and categorized it by state. Next, I found the Mental Health dataset (Mental Health Care in the Last 4 Weeks), which took mental health statistics from the same time period and categorized them by week and state. These datasets would be compatible since they could be connected through the state, start date, and end date columns, which detailed the state in which the data was collected from and the start and end dates of the week it was collected in.

After stepping away from the project for about a month to focus on other projects, I came back and took a deeper look at the 2 datasets. First, I found that the start and end dates did not match up between datasets. In fact, they didn't match up *within* datasets, as some timeframes were as little as 1 week and sometimes as large as 3. Furthermore, many of these time frames were not full weeks, which meant that there would need to be significant data cleaning and organization performed to combine the datasets. To find a solution, I looked at the Household Pulse Survey (Household Pulse Survey Data Tables), which is a 20 minute long online survey published by the U.S. Census Bureau that measures how emergent social and economic issues impacted households across the country. Being the source of the data from the Mental Health dataset, I tried to find alternate time tables or an explanation for why the intervals were uneven, but found nothing. Instead, I found that many of the features involved were useless for my endeavors. This meant that the only reliable features from the dataset were the "Indicator" [for mental health] and death totals. Preliminary analysis showed that the "Group" and "Subgroup" features had a large variety of different possible points. However, they turned out to be useless as about 2/3 of all rows had "By State" as the value for the "Group" value and the state name as

the “Subgroup” value. For these rows, “Group” and “Subgroup” would act as noise since the state is already found in the “State” feature. Furthermore, the other 1/3 states, regardless of their “Group” or “Subgroup” values, listed “United States” as the “State” value, meaning that the death totals would be heavily inflated compared to where the survey participants actually lived.

	Group	Subgroup	State	count
0	By Age	18 - 29 years	United States	152
1	By Age	30 - 39 years	United States	152
2	By Age	40 - 49 years	United States	152
3	By Age	50 - 59 years	United States	152
4	By Age	60 - 69 years	United States	152
5	By Age	70 - 79 years	United States	152
6	By Age	80 years and above	United States	152
7	By Disability status	With disability	United States	84
8	By Disability status	Without disability	United States	84
9	By Education	Bachelor's degree or higher	United States	152
10	By Education	High school diploma or GED	United States	152
11	By Education	Less than a high school diploma	United States	152
12	By Education	Some college/Associate's degree	United States	152
13	By Gender identity	Cis-gender Female	United States	52
14	By Gender identity	Cis-gender Male	United States	52
15	By Gender identity	Transgender	United States	52
16	By Presence of Symptoms of Anxiety/Depression	Did not experience symptoms of anxiety/depression in the past 4 weeks	United States	152
17	By Presence of Symptoms of Anxiety/Depression	Experienced symptoms of anxiety/depression in past 4 weeks	United States	152
18	By Race/Hispanic ethnicity	Hispanic or Latino	United States	152
19	By Race/Hispanic ethnicity	Non-Hispanic Asian, single race	United States	152
20	By Race/Hispanic ethnicity	Non-Hispanic Black, single race	United States	152
21	By Race/Hispanic ethnicity	Non-Hispanic White, single race	United States	152
22	By Race/Hispanic ethnicity	Non-Hispanic, other races and multiple races	United States	152
23	By Sex	Female	United States	152
24	By Sex	Male	United States	152
25	By Sexual orientation	Bisexual	United States	52
26	By Sexual orientation	Gay or lesbian	United States	52
27	By Sexual orientation	Straight	United States	52
28	By State	Alabama	Alabama	132
29	By State	Alaska	Alaska	132
30	By State	Arizona	Arizona	132
31	By State	Arkansas	Arkansas	132
32	By State	California	California	132
33	By State	Colorado	Colorado	132
34	By State	Connecticut	Connecticut	132
35	By State	Delaware	Delaware	132
36	By State	District of Columbia	District of Columbia	132
37	By State	Florida	Florida	132
38	By State	Georgia	Georgia	132
39	By State	Hawaii	Hawaii	132
40	By State	Idaho	Idaho	132
41	By State	Illinois	Illinois	132
42	By State	Indiana	Indiana	132
43	By State	Iowa	Iowa	132
44	By State	Kansas	Kansas	132
45	By State	Kentucky	Kentucky	132
46	By State	Louisiana	Louisiana	132
47	By State	Maine	Maine	132
48	By State	Maryland	Maryland	132
49	By State	Massachusetts	Massachusetts	132
50	By State	Michigan	Michigan	132
51	By State	Minnesota	Minnesota	132
52	By State	Mississippi	Mississippi	132
53	By State	Missouri	Missouri	132
54	By State	Montana	Montana	132
55	By State	Nebraska	Nebraska	132
56	By State	Nevada	Nevada	132
57	By State	New Hampshire	New Hampshire	132
58	By State	New Jersey	New Jersey	132
59	By State	New Mexico	New Mexico	132
60	By State	New York	New York	132
61	By State	North Carolina	North Carolina	132
62	By State	North Dakota	North Dakota	132
63	By State	Ohio	Ohio	132
64	By State	Oklahoma	Oklahoma	132
65	By State	Oregon	Oregon	132
66	By State	Pennsylvania	Pennsylvania	132
67	By State	Rhode Island	Rhode Island	132
68	By State	South Carolina	South Carolina	132
69	By State	South Dakota	South Dakota	132
70	By State	Tennessee	Tennessee	132
71	By State	Texas	Texas	132
72	By State	Utah	Utah	132
73	By State	Vermont	Vermont	132
74	By State	Virginia	Virginia	132
75	By State	Washington	Washington	132
76	By State	West Virginia	West Virginia	132
77	By State	Wisconsin	Wisconsin	132
78	By State	Wyoming	Wyoming	132
79	National Estimate	United States	United States	152

Figure 1. Unique combinations of “Group” and “Subgroup” values placed alongside “State” values and the number of times the combinations occurred in the data

Exploratory Analysis (5%):

Before attempting to combine the datasets, I needed to clean and organize the data to ensure that it would be compatible and only have useful information. First, I removed all unnecessary columns from the original datasets, ensuring that the only columns remaining were “Indicator”, “State”, “Time Period Start Date”, “Time Period End Date” for the Mental Health dataset and “Start Date”, “End Date”, “State”, “COVID-19 Deaths”, and “Total Deaths” for the COVID-19 dataset. “Indicator” refers to the mental health treatment that was or wasn’t taken by the participant, the start and end dates refer to the dates between which the survey was taken, “State” refers to the state that the participant lived in, “COVID-19 Deaths” refers to the number of deaths attributed to COVID-19 occurred between the start and end dates, and “Total Deaths” refers to the number of deaths attributed to COVID-19 and other respiratory diseases during that time frame. Next, I removed all rows with NA values within the data to ensure that the dataset was complete. Finally, I converted all dates to datetime objects to ensure that they would be compatible regardless of the date taking notation used.

Next, I created a new dailyCovid dataset which stores information from the COVID-19 dataset but on a day to day basis. For each row in the COVID-19 dataset, I found the inclusive range between the start and end dates and took the mean number of “COVID-19 Deaths” and “Total Deaths” in said range. Then, I populated the dailyCovid dataset with values for the “State”, “Date”, “COVID-19 Deaths” and “Total Deaths” columns. The state from the COVID-19 dataset would be stored in “State”, each date from a date range found in the COVID-19 dataset would be stored in “Date”, and the mean number of “COVID-19 Deaths” and “Total Deaths” between dates in the date range would be stored in similarly named columns.

```
Total rows in dailyCovidData before duplicate removal: 411659  
Total rows in dailyCovidData after duplicate removal: 113022
```

Figure 2. Total rows present in the dailyCovid dataset before and after duplicate removal

This created 411,659 rows. However, since participants from the same state could have filled out the survey during time periods with overlapping dates. Due to recording discrepancies, death totals could be different between these entries. Thus, for every set of rows that had the same “State” and “Date” values, I replaced them with a single row containing the same “State” and “Date” value along with the mean “COVID-19 Deaths” and “Total Deaths” values for each of the rows in the same grouping. This significantly reduced noise in the dataset as the final result was 113,022 rows.

I finished up the data organization by creating a finalData dataset, which took the “State”, “Start Date”, “End Date”, and “Indicator” values from each row in the Mental Health Dataset. Then, I placed the sum of all “COVID-19 Deaths” from rows in the dailyCovid dataset with dates between the “Start Date” and “End Date” values of the Mental Health dataset. This process was also done with “Total Deaths”. Then, I created the “Cumulative COVID-19 Deaths” and “Cumulative Total Deaths” columns, which were populated with the cumulative amount of deaths that occurred from the first date in the dailyCovid dataset until the “End Date” in the Mental Health dataset. Both the Mental Health and finalData (herein referred to as “the data”) datasets had 10,404 rows, which means that the data organization was performed correctly.

```
Total rows in finalData: 10404  
Total rows mentalHealthData: 10404
```

Figure 3. Total rows present in the finalData dataset and Mental Health dataset

State	
United States	3672
Alabama	132
Alaska	132
Arizona	132
Arkansas	132
California	132
Colorado	132
Connecticut	132
Delaware	132
District of Columbia	132
Florida	132
Georgia	132
Hawaii	132
Idaho	132
Illinois	132
Indiana	132
Iowa	132
Kansas	132
Kentucky	132
Louisiana	132
Maine	132
Maryland	132
Massachusetts	132
Michigan	132
Minnesota	132
Mississippi	132
Missouri	132
Montana	132
Nebraska	132
Nevada	132
New Hampshire	132
New Jersey	132
New Mexico	132
New York	132
North Carolina	132
North Dakota	132
Ohio	132
Oklahoma	132
Oregon	132
Pennsylvania	132
Rhode Island	132
South Carolina	132
South Dakota	132
Tennessee	132
Texas	132
Utah	132
Vermont	132
Virginia	132
Washington	132
West Virginia	132
Wisconsin	132
Wyoming	132

Figure 4. Distribution of values in “States” Column of the data

Further indication that the data organization was performed correctly can be found in the breakdown of “State” in the data (Figure 4). “United States” appears 3672 times and all other states appear 132 times, which matches the counts from the Mental Health dataset (Figure 1).

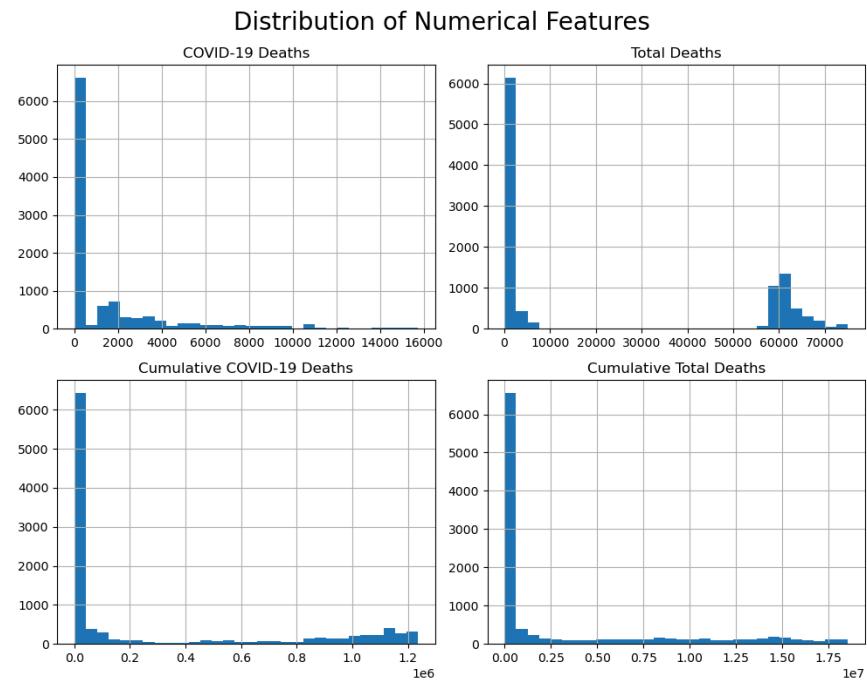


Figure 5. Distribution of Numerical Features in the data via histograms

All distributions of numerical features (Figure 5) follow the same trend of experiencing a high volume of instances with relatively low death counts and a tiny volume of instances for the steadily increasing death totals. Since the data maps late 2019 to late 2025, it can be assumed that the large number of low death counts is due to the amount of survey responses retrieved before and after the COVID-19 pandemic.

The boxplot of the numerical data (Figure 6) shows only “COVID-19 Deaths” and “Cumulative Total Deaths” experienced a large number of high valued outliers. This can be attributed to the large spikes in COVID-19 deaths in 2020 - 2022. Likewise, “Cumulative Total Deaths” would experience outliers in the same time period since COVID-19 deaths are included in these totals. It can be assumed that “Cumulative COVID-19 Deaths” didn’t experience outliers since the number was always steadily increasing or plateauing. Similarly, “Total Deaths” likely experienced similar death counts in smaller time frames over the years.

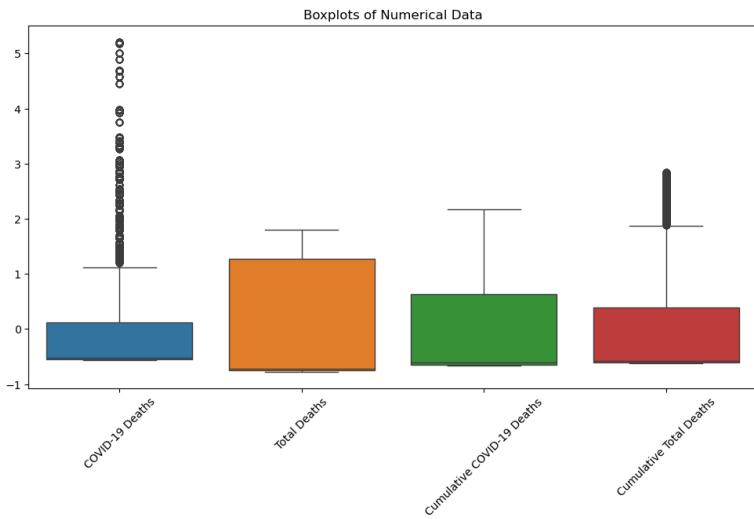
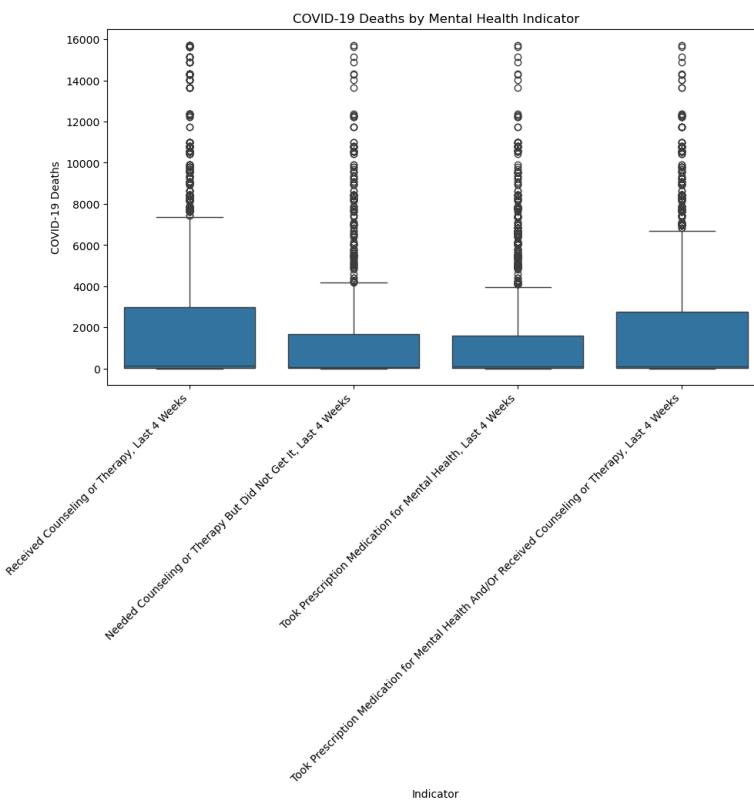
**Figure 6. Boxplot of Numerical Features in the data****Figure 7. Boxplot of COVID-19 Deaths by Mental Health Indicator in the data**

Figure 7 features a boxplot depicting COVID-19 Deaths by Mental Health Indicator found within the data, and it is clear that as the number of COVID-19 deaths rise so does the number of outliers present in mental health indicators.

Figures 8-15 show the timeline of each death statistic over the last 5 years organized by state. To display these figures, rows with “United States” as a state were removed because it vastly overshadowed the statistics of even the largest individual states. Figures 9, 11, 13, and 15 depict the same information as Figures 8, 10, 12, and 14 respectively, except they only display 5 states. Four of the states represent different quantiles (25%, 50%, 75%, and maximum) for the given statistic, and the last state represented is my home state, New Hampshire. I included my home state because while not statistically significant, it illustrates why I originally had such a gap in knowledge about the severity of COVID-19 prior to coming to RPI, since there are very few deaths related to COVID-19 compared to other states. Overall, it can be seen that the states which suffered the most deaths in any category were also those with some of the largest state populations, eluding to the fact that these numbers likely represent a proportional increase rather than any missteps by the state.

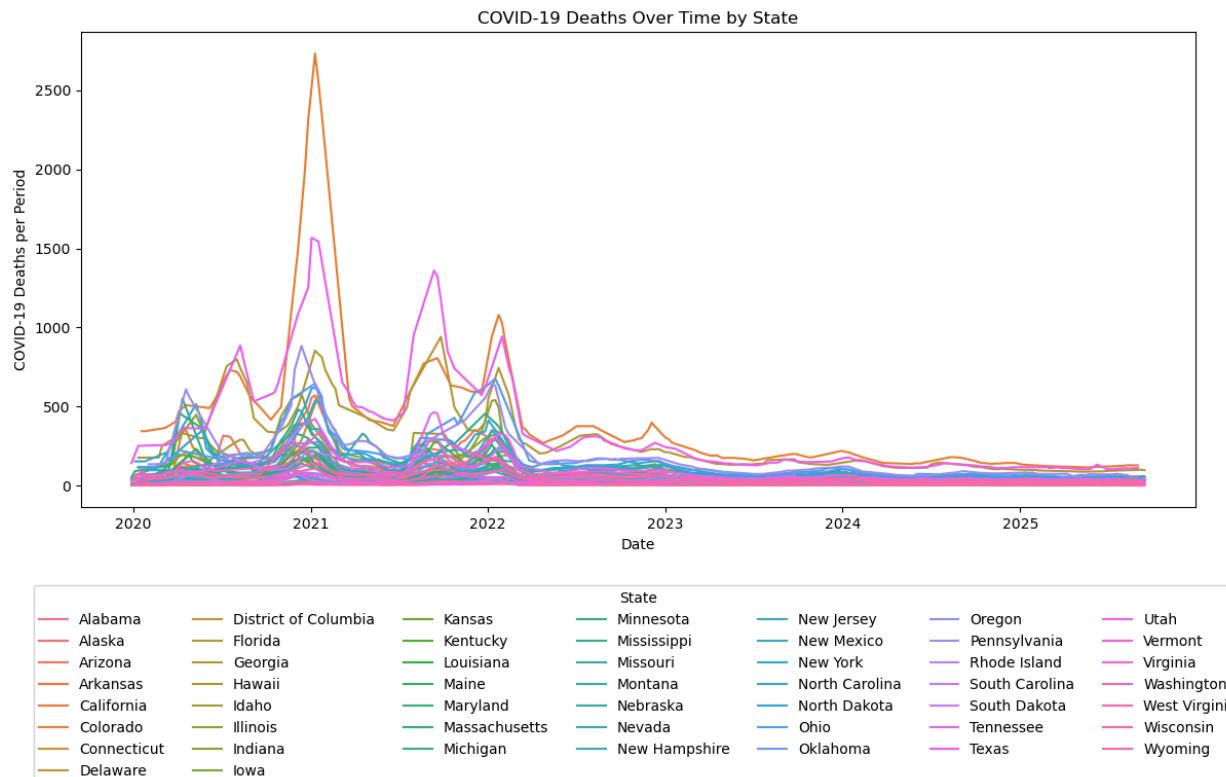


Figure 8. Scatterplot of COVID-19 Deaths over time by state

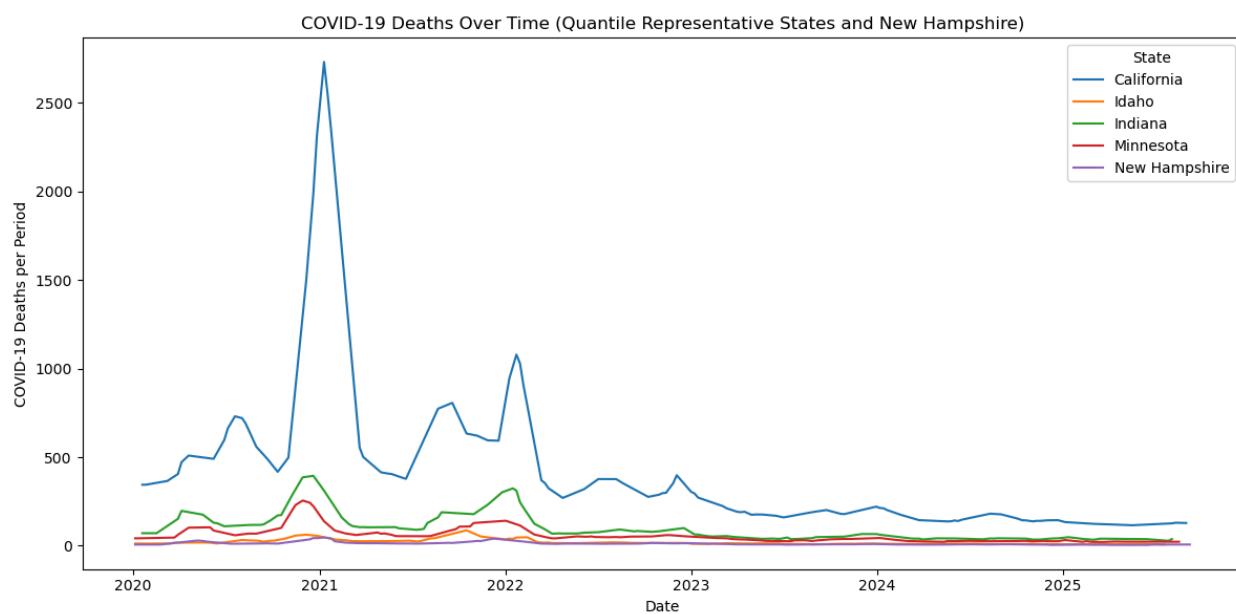


Figure 9. Scatterplot of COVID-19 Deaths over time by quantile representative states and New Hampshire

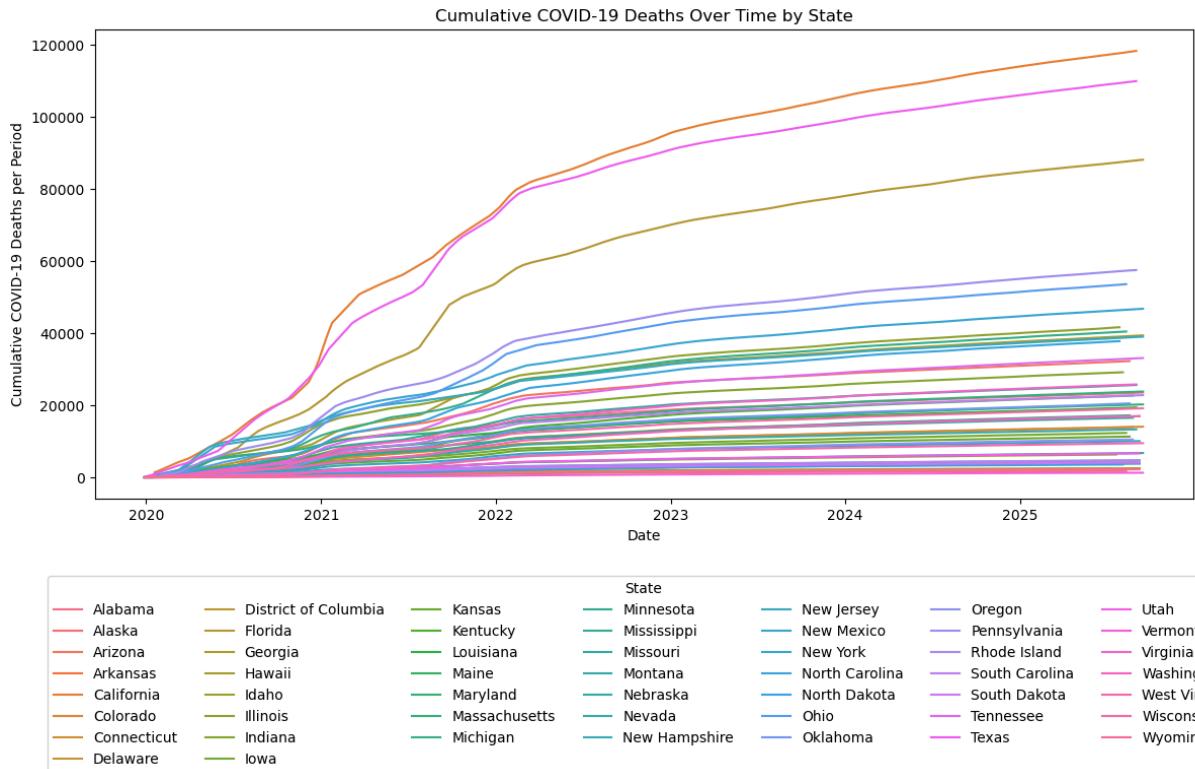


Figure 10. Scatterplot of Cumulative COVID-19 Deaths over time by state

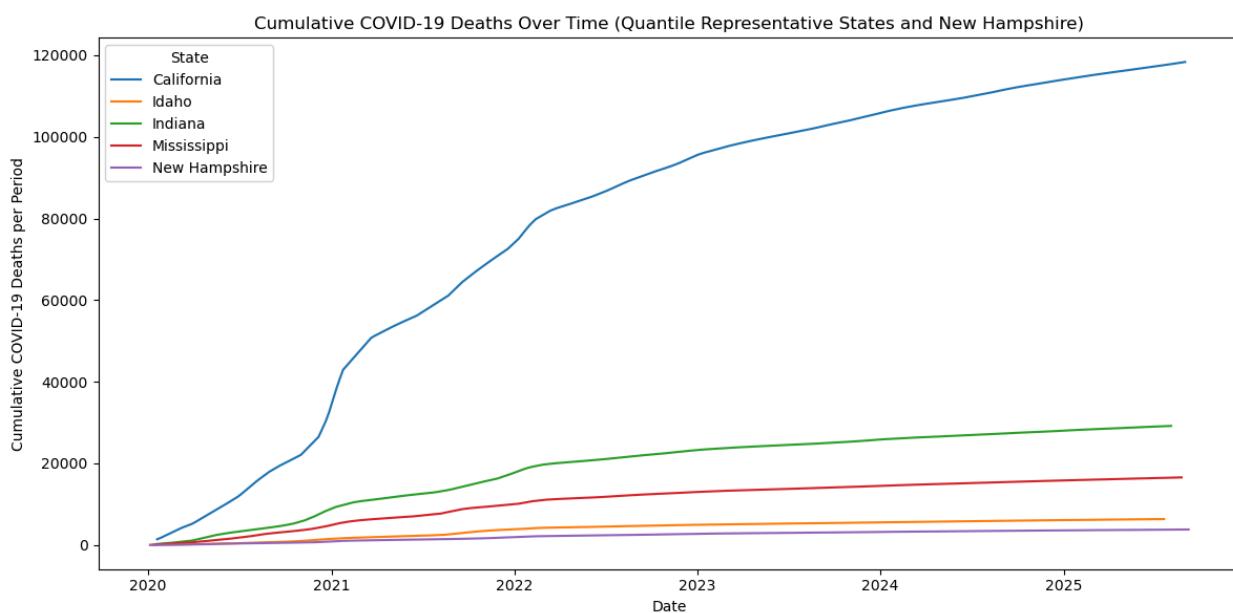


Figure 11. Scatterplot of Cumulative COVID-19 Deaths over time by quantile representative states and New Hampshire

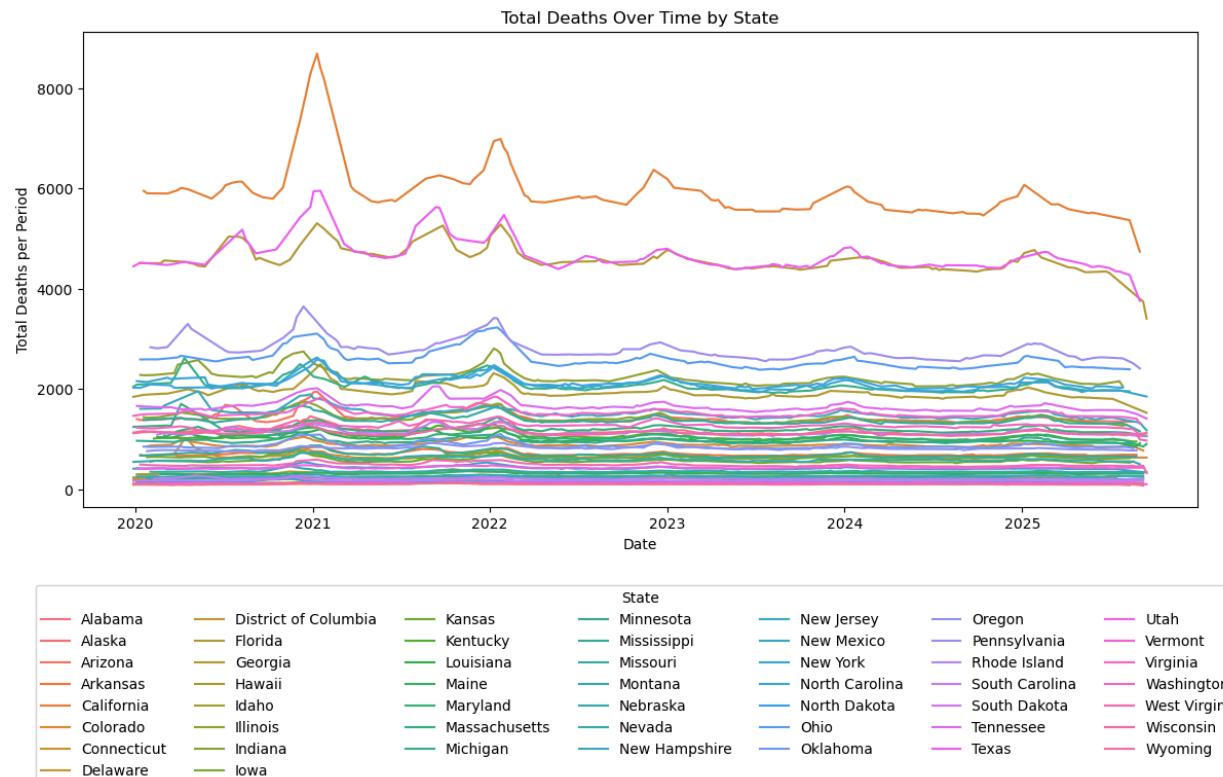


Figure 11. Scatterplot of Total Deaths over time by state

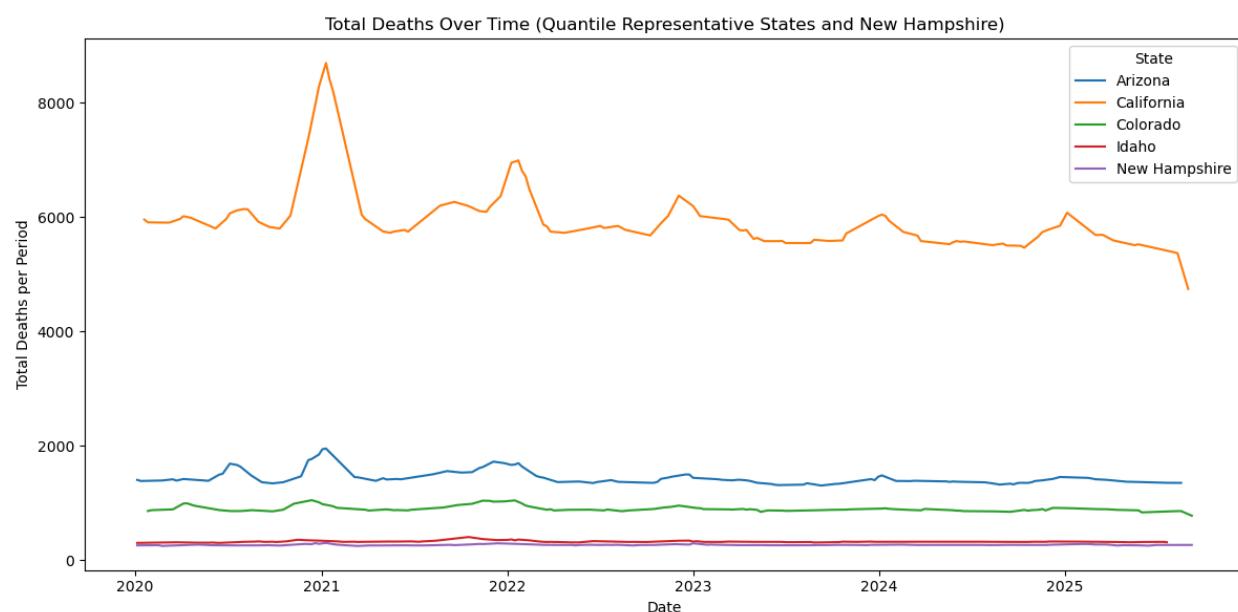


Figure 12. Scatterplot of Total Deaths over time by quantile representative states and New Hampshire

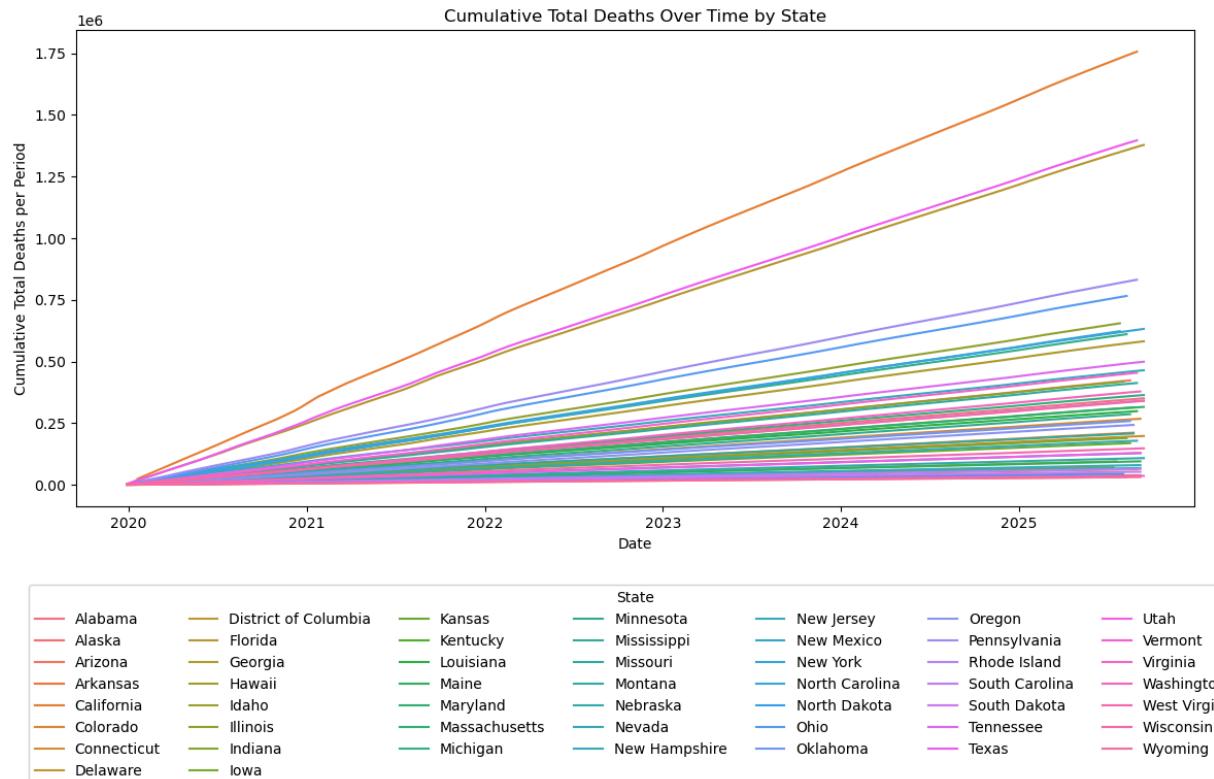


Figure 13. Scatterplot of Cumulative Total Deaths over time by state

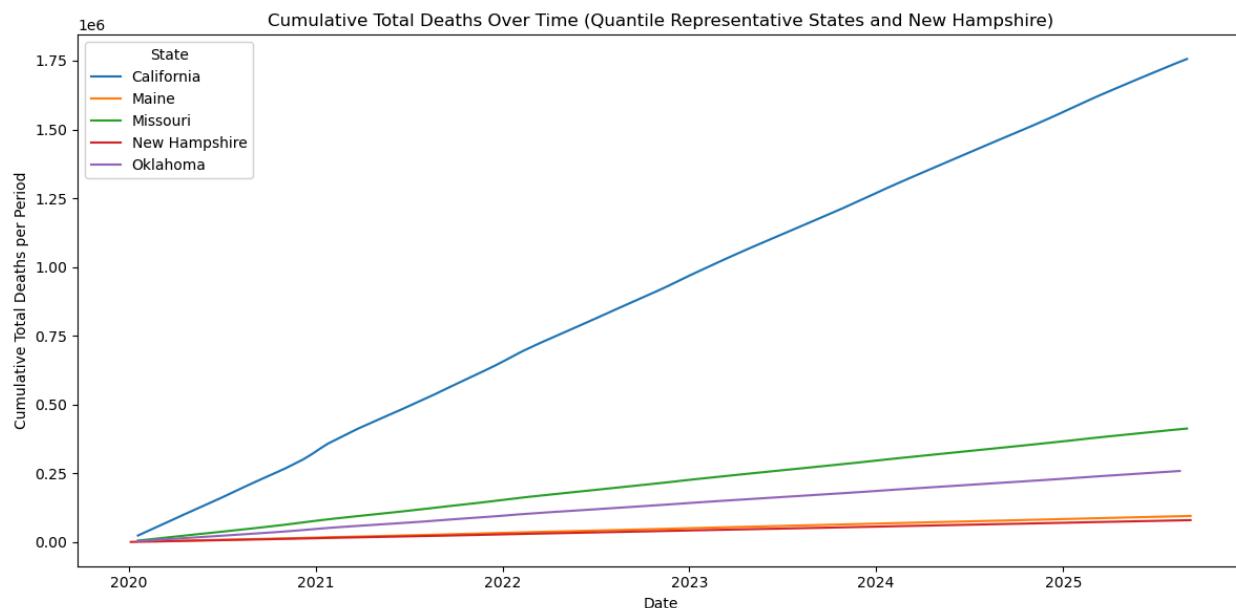


Figure 14. Scatterplot of Cumulative Total Deaths over time by quantile representative states and New Hampshire

Alex Litchfield

12/12/2025

Data Analytics

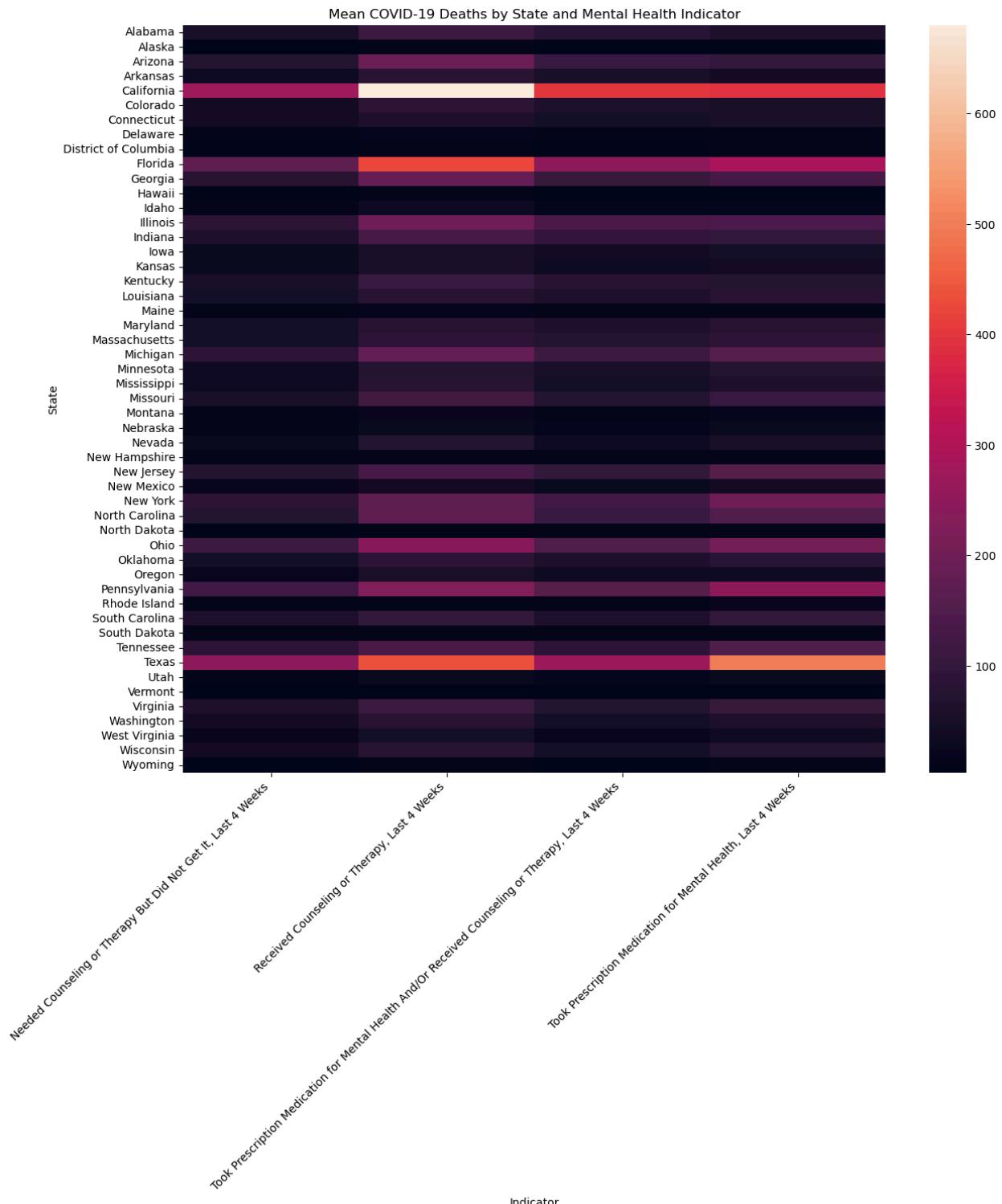


Figure 15. Heatmap of Mean COVID-19 Deaths by State and Mental Health Indicator

Model Development and Application of model(s) (12%):

I chose to implement 5 different types of models. The first four models, Logistic Regression, Random Forest, Classifier, K-Nearest-Neighbors (KNN), and Support Vector Machine (SVM) with a polynomial kernel, are all supervised classifier models with the target variable of "Indicator" [for mental health]. They also use standardized numeric death counts and one-hot encoded categorical variables with an 80/20 stratified train/test split. The fifth model is K-Means Clustering with Principal Component Analysis (PCA) Visualization. For K-Means I used silhouette score and elbow method analysis to find natural groupings and find whether clusters align with the different "Indicator" types. Classification performance was compared using accuracy, precision, recall, and F1 score. Cluster summaries were used to show meaningful distributions of death totals and indicator types within the clusters.

The numeric features include "COVID-19 Deaths", "Total Deaths", "Cumulative COVID-19 Deaths", and "Cumulative Total Deaths" and the categorical features include "State". Anything that could utilize a seed was provided a seed of 42 to ensure reproducibility upon subsequent runs. StandardScaler() was used for numeric features and OneHotEncoder() was used for the categorical features prior to deployment of all models. ColumnTransformer() and Pipeline() were used to ensure that an identical pipeline was created for preprocessing prior to all model deployment. I chose these models because they were all ones that were taught in class, and the kernel used in SVM was chosen due to having the best performance compared to the other kernels.

	accuracy	precision	\
Logistic Regression	0.282	0.282	
Logistic Regression (without U.S. as a State)	0.398	0.397	
Random Forest Classifier	0.437	0.437	
Random Forest Classifier (without U.S. as a State)	0.432	0.432	
KNN Classifier	0.437	0.439	
KNN Classifier (without U.S. as a State)	0.466	0.468	
SVM	0.310	0.383	
SVM (without U.S. as a State)	0.336	0.369	

	recall	f1score	
Logistic Regression	0.282	0.281	
Logistic Regression (without U.S. as a State)	0.398	0.394	
Random Forest Classifier	0.437	0.437	
Random Forest Classifier (without U.S. as a State)	0.432	0.432	
KNN Classifier	0.437	0.436	
KNN Classifier (without U.S. as a State)	0.466	0.464	
SVM	0.310	0.287	
SVM (without U.S. as a State)	0.336	0.319	

Figure 16. Classifier Model Metrics Comparison

Figure 16 shows the accuracy, precision, recall, and F1 score metrics for each of the classification models. Since I removed all rows with "U.S." as a value for "State" while creating plots due to the large difference in scale, I assumed that it might make a large difference in model training too. Thus, I ran 2 versions of each model - one that included "U.S" as a value for "State" and one that did not. When all data was included KNN performed the best in all metrics and achieved about 46.6% accuracy. That was followed by Random Forest, SVM polynomial kernel, and Logistic Regression. When rows with "U.S" as the state were dropped, Random Forest and KNN performed equally well, achieving a peak of about 43.7% accuracy. Following

this was Logistic Regression and SVM. Removing “U.S.” as a state improved overall performance in all models except for Random Forest, which suffered a slight dip in performance. Logistic Regression in particular benefited greatly from this change, which makes sense due to less variability in the feature types.

-- Logistic Regression				
	0	1	2	3
0	156	83	138	143
1	126	140	131	123
2	137	111	157	116
3	140	142	105	133

-- Logistic Regression (without U.S. as a State)				
	0	1	2	3
0	173	42	65	57
1	52	118	105	61
2	90	67	143	37
3	104	89	42	102

Figure 17. Confusion Matrices of Logistic Regression Models

-- Random Forest Classifier				
	0	1	2	3
0	229	67	118	106
1	73	225	90	132
2	94	131	232	64
3	127	100	69	224

-- Random Forest Classifier (without U.S. as a State)				
	0	1	2	3
0	147	30	78	82
1	41	157	63	75
2	80	81	130	46
3	68	68	53	148

Figure 18. Confusion Matrices of Random Forest Models

-- KNN Classifier				
	0	1	2	3
0	254	81	108	77
1	92	238	83	107
2	115	151	200	55
3	129	113	61	217

-- KNN Classifier (without U.S. as a State)				
	0	1	2	3
0	174	40	70	53
1	53	183	43	57
2	72	106	131	28
3	82	67	48	140

Figure 19. Confusion Matrices of KNN Models

-- SVM				
	0	1	2	3
0	109	315	29	67
1	45	348	18	109
2	36	330	83	72
3	87	312	15	106

-- SVM (without U.S. as a State)				
	0	1	2	3
0	46	50	185	56
1	11	99	153	73
2	18	66	189	64
3	24	80	115	118

Figure 20. Confusion Matrices of SVM Models

Figures 17-20 display the confusion matrices between the different classification models. At a glance, the numbers in each confusion matrix look almost evenly distributed through, with a slight increase in the size of the numbers along the diagonal line starting at the top left. This means that while a sizable chunk of the predictions were true positives, the majority of the predictions were incorrect, leading to the below 50% accuracy on all models. A significant amount of miscalculation like this implies that features heavily overlap across categories and the models struggle to separate them. It also means each class is hard to identify, further leading to inseparability.

Despite the improvements present between models, the highest accuracy achieved between all models was only about 46.6%. Therefore, it is safe to say that this hypothesis is not possible given the following data. This is likely due to a lack of relevant features available in the original datasets found through the CDC. As such, the only available features to predict off of

were death totals and state, which may have been more useful when coupled with information like sex, race etc. That being said, even if these potential features did improve model accuracy, one could argue that it defeats the purpose since the hypothesis implied that mental health indicators could be predicted off of COVID-19 death rates alone. Each metric used a weighted average to reflect class imbalances.

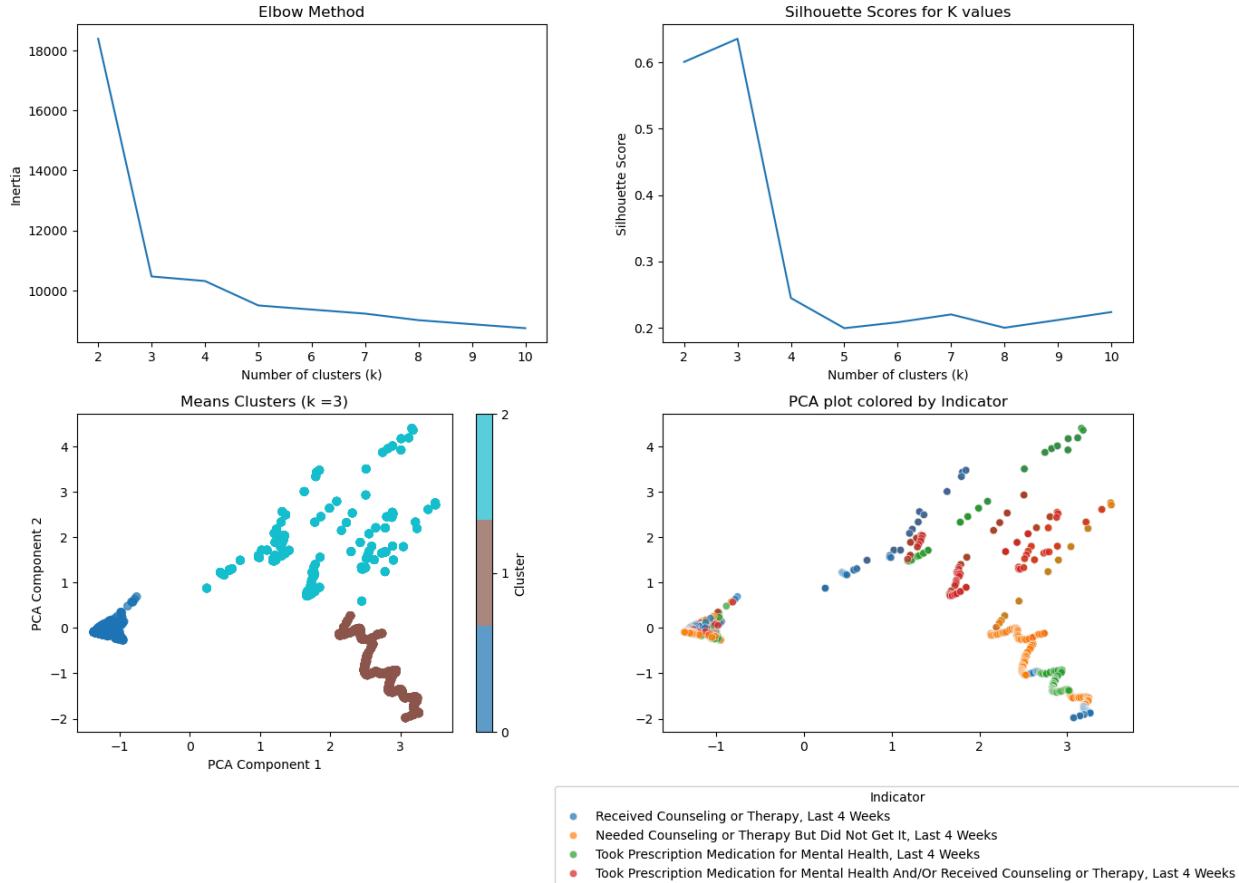


Figure 21. Elbow Method plot for number of K values plot (top left), Silhouette Scores plot for K values plot (top right), Cluster plot via PCA (bottom left), PCA plot colored by Indicator (bottom right) - All data included

The output from the K-Means model was able to shed some light on why the classification models did not perform well. First, I found the inertia values and silhouette scores for K values 2 through 10. Once plotted, it was easy to see that the optimal K value for the model when "U.S" was included as a state was K = 3 due to the elbow in the elbow method plot in Figure 21 and the peak of the silhouette scores plot in Figure 21. Once this was determined, the PCA visualization of the clustering was found in the bottom left plot of Figure 21. The points in all clusters are globally separated, which shows that the features contain different groups and that the projection maintained enough variance to show a meaningful structure. However, the large distance between some points in clusters signifies that the data is very spread out and features have high variability. This is to be expected due to the inclusion of "U.S" as a state, as it effectively creates outliers across the board. The plot on the bottom right of Figure 21 shows the

mental health indicator for each point in the clusters. This plot displays clear groupings but fails to match those in the original PCA visualization plot. It also shows lots of overlap which implies that there was not enough information to differentiate the indicators.

Cluster	COVID-19 Deaths	Total Deaths	Cumulative COVID-19 Deaths
0	79.687813	1194.495502	1.571984e+04
1	2212.433174	60017.413079	1.068219e+06
2	7160.340143	65026.941027	3.612618e+05
Cluster	Cumulative Total Deaths		
0	1.851472e+05		
1	1.286901e+07		
2	3.502721e+06		

Figure 22. Average by cluster for each numeric feature - with “U.S”

---- Distribution of Indicators by cluster		
Cluster	Indicator	
0	Needed Counseling or Therapy But Did Not Get It, Last 4 Weeks	0.250000
	Received Counseling or Therapy, Last 4 Weeks	0.250000
	Took Prescription Medication for Mental Health And/Or Received Counseling or Therapy, Last 4 Weeks	0.250000
1	Took Prescription Medication for Mental Health, Last 4 Weeks	0.250000
	Needed Counseling or Therapy But Did Not Get It, Last 4 Weeks	0.334242
	Took Prescription Medication for Mental Health And/Or Received Counseling or Therapy, Last 4 Weeks	0.271571
	Took Prescription Medication for Mental Health, Last 4 Weeks	0.256585
2	Received Counseling or Therapy, Last 4 Weeks	0.137602
	Received Counseling or Therapy, Last 4 Weeks	0.418367
	Took Prescription Medication for Mental Health, Last 4 Weeks	0.240136
	Took Prescription Medication for Mental Health And/Or Received Counseling or Therapy, Last 4 Weeks	0.217687
	Needed Counseling or Therapy But Did Not Get It, Last 4 Weeks	0.123810

Figure 23. Distribution of Indicators per cluster - with “U.S”

---- Counts for each unique Indicator per cluster		
Indicator	Needed Counseling or Therapy But Did Not Get It, Last 4 Weeks	
Cluster		
0	1683	
1	736	
2	182	
Indicator	Received Counseling or Therapy, Last 4 Weeks	
Cluster		
0	1683	
1	303	
2	615	
Indicator	Took Prescription Medication for Mental Health And/Or Received Counseling or Therapy, Last 4 Weeks	
Cluster		
0	1683	
1	598	
2	320	
Indicator	Took Prescription Medication for Mental Health, Last 4 Weeks	
Cluster		
0	1683	
1	565	
2	353	

Figure 24. Counts for each Indicator per cluster - with “U.S”

Interestingly, the K-means model that was run without rows showing “U.S” as a state (Figure 25) performed worse than the original. I assumed that because the other models performed better with this change so would the K-means model. Upon further reflection, however, it is to be expected that the second K-means model would perform worse due to the increased variation. Without the “U.S” state, a major factor that determined cluster dominance shifted, and since all other states are equally distributed, it was unlikely that any meaningful clusters would form. The elbow method failed to show any meaningful bend in the plot, and the

The averages for each numeric feature by cluster (Figure 22) show that the death totals have a large difference in average value. This explains why the clusters were globally separated. The distribution of indicators by cluster (Figure 23) and indicator counts per cluster (Figure 24) show that each cluster has a significant amount of points from each indicator, typically having a similar proportional distribution between clusters. These imply that there is no dominant indicator per cluster, which is not ideal. This further confirms that there is not enough variance to differentiate indicators within clusters.

silhouette scores showed that the highest score was $K = 2$. The PCA visualization plot in the bottom left shows a far worse distribution than the previous iteration of the model, as one cluster is very compact and one is very spread out. Like before, this shows that there is just enough variance to provide a structure, but not enough to create meaningful clusters based on the features given. The plot in the bottom right confirms that the clusters were not meaningful, as there is little to no separation between indicators.

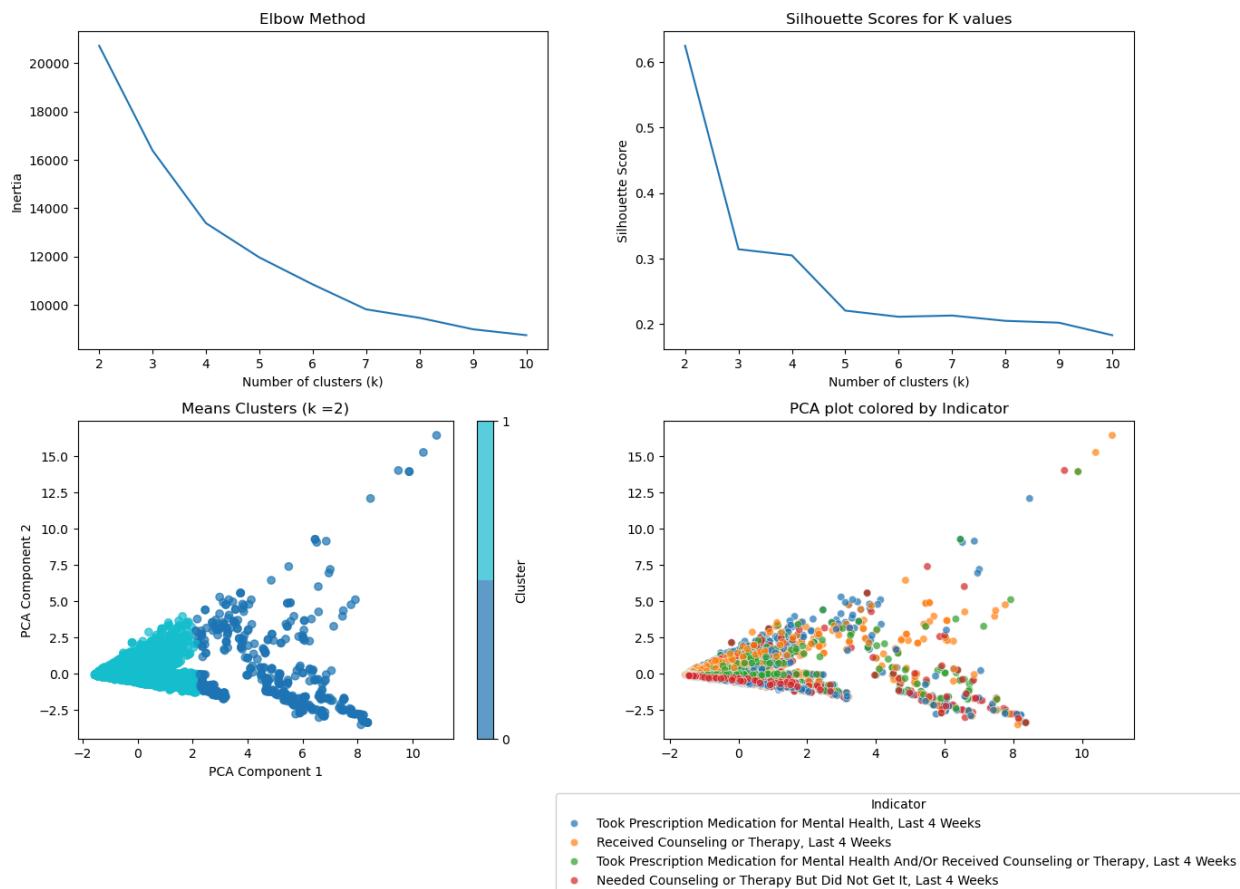


Figure 25. Elbow Method plot for number of K values plot (top left), Silhouette Scores plot for K values plot (top right), Cluster plot via PCA (bottom left), PCA plot colored by Indicator (bottom right) - without “U.S” as a State

The averages for each numeric feature by cluster (Figure 26) once again show that the death totals have a large difference in average value, explaining the global separation of clusters. The distribution of indicators by cluster (Figure 27) and indicator counts per cluster (Figure 28) show that each cluster has a significant amount of points from each indicator, typically having a similar proportional distribution between clusters. Since there is no dominant indicator in any of the clusters like before, there must still not be enough variance to differentiate indicators within clusters. Based on the distribution seen in these figures, I feel that the data became more skewed without rows with “U.S” as a state, since it supplied about 1/3 of all points in the data and basically defined one or two clusters due to the outliers it created. I am not confident in the results due to the poor performance of the models. I feel as though the data fed to the models was lacking in features and prevented class differentiation.

---- Averages by cluster for each numeric feature:			
cluster	COVID-19 Deaths	Total Deaths	Cumulative COVID-19 Deaths \
0	309.586622	4441.085873	66717.362342
1	60.403112	922.160357	11441.987369
Cumulative Total Deaths			
cluster			
0	754323.046065		
1	137402.726830		

Figure 26. Averages by cluster for each numeric feature - no “U.S”

---- Distribution of Indicators by cluster			
Cluster	Indicator		
0	Needed Counseling or Therapy But Did Not Get It, Last 4 Weeks	0.284069	
	Took Prescription Medication for Mental Health And/Or Received Counseling or Therapy, Last 4 Weeks	0.266795	
	Received Counseling or Therapy, Last 4 Weeks	0.232246	
1	Took Prescription Medication for Mental Health, Last 4 Weeks	0.216891	
	Took Prescription Medication for Mental Health, Last 4 Weeks	0.252777	
	Received Counseling or Therapy, Last 4 Weeks	0.251489	
	Took Prescription Medication for Mental Health And/Or Received Counseling or Therapy, Last 4 Weeks	0.248591	
	Needed Counseling or Therapy But Did Not Get It, Last 4 Weeks	0.247142	
Name: proportion, dtype: float64			

Figure 27. Distribution of Indicators per cluster - no “U.S”

---- counts for each unique Indicator per cluster			
Indicator	cluster		
Needed Counseling or Therapy But Did Not Get It, Last 4 Weeks	0	148	
	1	1535	
Indicator Received Counseling or Therapy, Last 4 Weeks \			
Received Counseling or Therapy, Last 4 Weeks	0	121	
	1	1562	
Indicator Took Prescription Medication for Mental Health And/Or Received Counseling or Therapy, Last 4 Weeks \			
Took Prescription Medication for Mental Health And/Or Received Counseling or Therapy, Last 4 Weeks	0	139	
	1	1544	
Indicator Took Prescription Medication for Mental Health, Last 4 Weeks			
Took Prescription Medication for Mental Health, Last 4 Weeks	0	113	
	1	1570	

Figure 28. Counts for each Indicator per cluster - no “U.S”

with fine tuning the SVM model for many hours and failed to achieve a version of the model which via fine tuning would finish running in 10 minutes and did not bring my laptop’s CPU temperature to over 165°F. After that, my main method of experimentation was through finding different models that could use a similar pipeline of data to ensure that it could run smoothly and efficiently on my system. After I began my preliminary analysis of the CDC datasets, I became much less confident in my ability to find a result that would prove my hypothesis. If I were to perform a subsequent exploration of this topic, I would look for better defined datasets with more features. Alternatively, I could continue to use the datasets I have and once again look for datasets that can be linked via the state and time frame columns. Regardless, the goal would be to find a larger number of useful features to feed the models for predictions.

Conclusions and

Discussion (3%):

My hypothesis was unable to be proven correct due to the lack of usable features to train the data on. Should I find another dataset that includes similar information along with other relevant fields, I feel as though the hypothesis could be proven correct. That being said, for the purposes of this project, the results are clear. None of the classification models or K-means clustering were able to predict mental health indicators from COVID-19 mortality rate. I do not feel that the models were poorly chosen. It is unlikely that I would have been able to find a better model suited for this data than KNN and Random Forest. Given more time and resources, the models could have been tuned to provide greater output. I experimented

Citations:

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