S&DS 563/S&DS 363 Final Project

15 May 2021

Introduction

With the nadir of the SARS-CoV-2 pandemic finally subsiding, the task of understanding the epidemiological factors contributing to the propagation of COVID-19 has only begun. Understanding relationships between COVID-19 spread prevention and socioeconomic variables will prove vital to inform us of how to mitigate the propagation of the next pandemic. This report aims to understand how the economic, education, behavioral, and population data for the 3141 U.S. counties relate to COVID-19 infection and death rate data.

We acknowledge that the impact of and response to COVID-19 has been very different from county to county in the United States. Looking at the current COVID-19 vaccination data in mid-May 2020, we note that the vaccination rate for ages 18+ ranges drastically from 11% in some counties in Louisiana to 74% in some counties in New York. Our guiding question is: Who is the most vulnerable to COVID-19 infection and death? This knowledge will guide public health efforts as we continue to fight against the spread of COVID-19. Knowledge of what socioeconomic factors put people at risk will allow us to prioritize our vaccination and education efforts from those who need it the most and will also let us take a step back to acknowledge the systemic health inequalities in our country.

Design and Primary Questions

This report deploys three multivariate techniques to examine the following questions:

1. How do the 3141 counties differ from one another, i.e., how do the socioeconomic and COVID-19 data relate to one another when distinguishing U.S. counties? Principal component analysis (PCA) will help to reduce the dimensionality of our large dataset, increasing interpretability of underlying trends between clusters of variables. This metric technique works on the columns of our dataset to reduce them into composite variables and make them more interpretable.
2. Which U.S. counties are similar to one another? Cluster analysis will enable the clustering of counties into a discrete number of groups based on similar socioeconomic and COVID-19 data. This metric technique works on the rows of our dataset to find similar groups of observations.
3. Which U.S. states are similar to one another? Ordination techniques on aggregate state data are deployed to understand how the states differ from one another with respect to these socioeconomic and COVID-19 variables. This technique works on both the columns and rows of our dataset to visualize which rows and column points are similar in lower-dimensional space.

Using these techniques, we will be able to better understand our variables, our observations, and the interactions between our variables and observations. Who is most vulnerable to COVID-19 infection and death? This allows us to direct resources to protecting these vulnerable populations.

Data

The dataset referenced in this report includes COVID-19 infection and death statistics from U.S. counties (sourced from Johns Hopkins, as of 28 April 2021), combined with economic, education, and population data (sourced from various government agencies) and also survey responses about mask-wearing frequencies

(sourced from NYT) for a total of 3141 complete observations on 10 continuous variables and 6 categorical variables. Continuous variables were rescaled as percentages of county population.

- **6 categorical variables**: FIPS, county name, state name, rural urban type, rural urban code, economic typology
- **9 continuous variables**: "Always" wear mask survey response percent, unemployment rate, median household income, percent poverty, percent of adults with less than a high school education, death rate, percent civilian labor force, percent of county population that has had confirmed COVID-19 cases, and percent of county population that has died from COVID-19.

[1] "FIPS" = State-County FIPS Code; Categorical (identifier)

[2] "County_Name" = US County Name; Categorical (identifier)

[3] "State_Name" = US State Name; Categorical

[4] "Rural_Urban_Type" = Regrouping of Rural-Urban Codes (2013) numbered 1-9 according to descriptions provided by the USDA. See variable [5]. Regroup codes 1 through 9 into three groups: (1) "Urban" for codes 1-3, (2) "Suburban" for codes 4-6, and (3) "Rural" for codes 7-9; Categorical (1-3)

[5] "Rural_Urban_Code_2013" = Rural-urban Continuum Code, 2013; (https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/); Categorical (1-9)

[6] "Economic_Typology_2015" = County economic types, 2015 edition (https://www.ers.usda.gov/data-products/county-typology-codes/); Non-overlapping economic-dependence county indicator. 0=Nonspecialized 1=Farm-dependent 2=Mining-dependent 3=Manufacturing-dependent 4=Federal/State government-dependent 5=Recreation; Categorical (0-5)

[7] "Always_Wear_Mask_Survey" = "Always" response. The New York Times administered a survey to 250,000 Americans from July 2 to July 14 asking the following question: How often do you wear a mask in public when you expect to be within six feet of another person?; Continuous (%)

[8] "Unemployment_Rate_2019" = Unemployment rate, 2019; Continuous (%)

[9] "Median_Household_Income_2019" = Estimate of median household Income, 2019; Continous ($)

[10] "Percent_Poverty_2019" = Estimate of people of all ages in poverty 2019; Continuous (%)

[11] "Percent_Adults_Less_Than_HS" = Percent of adults with less than a high school diploma, 2014-18

[12] "Death_Rate_2019" = Death rate in period 7/1/2018 to 6/30/2019; Continuous (%)

[13] "Civilian_Labor_Force_2019_as_pct" = Civilian labor force annual average, 2019, expressed as percent; Continuous (%)

[14] "Covid_Confirmed_Cases_as_pct" = Cumulative sum of COVID-19 cases expressed as percent. Reported from Johns Hopkins on 28 April 2021; Continuous (%)

[15] "Covid_Deaths_as_pct" = Cumulative sum of COVID-19 deaths expressed as percent. Reported from Johns Hopkins on 28 April 2021; Continuous (%)

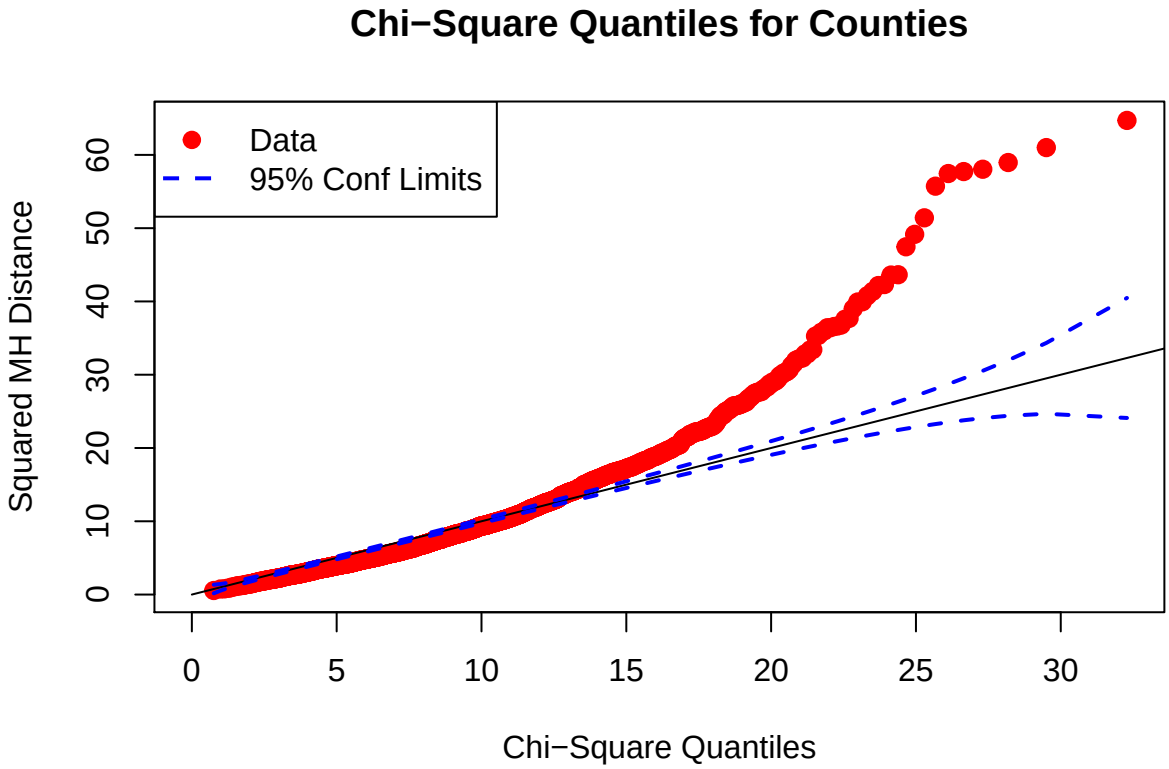
Descriptive Plots and Summary Statistics

Data Transformation

We made normal quantile plots for each of the 9 continuous variables in the dataset. This revealed that most variables initially did not have a univariate normal distribution. Taking the log-transform of the 10 continuous variables helped most variables have more linear quantile plots. Note that we also standardized the continuous variables since they were measured on different scales. Moreover, for death rate, percent COVID-19 cases, and percent COVID-19 deaths, a 1.5 x IQR outlier exclusion method was applied to enable these variables to take on more normal univariate distributions. Note that the outlier exclusion method

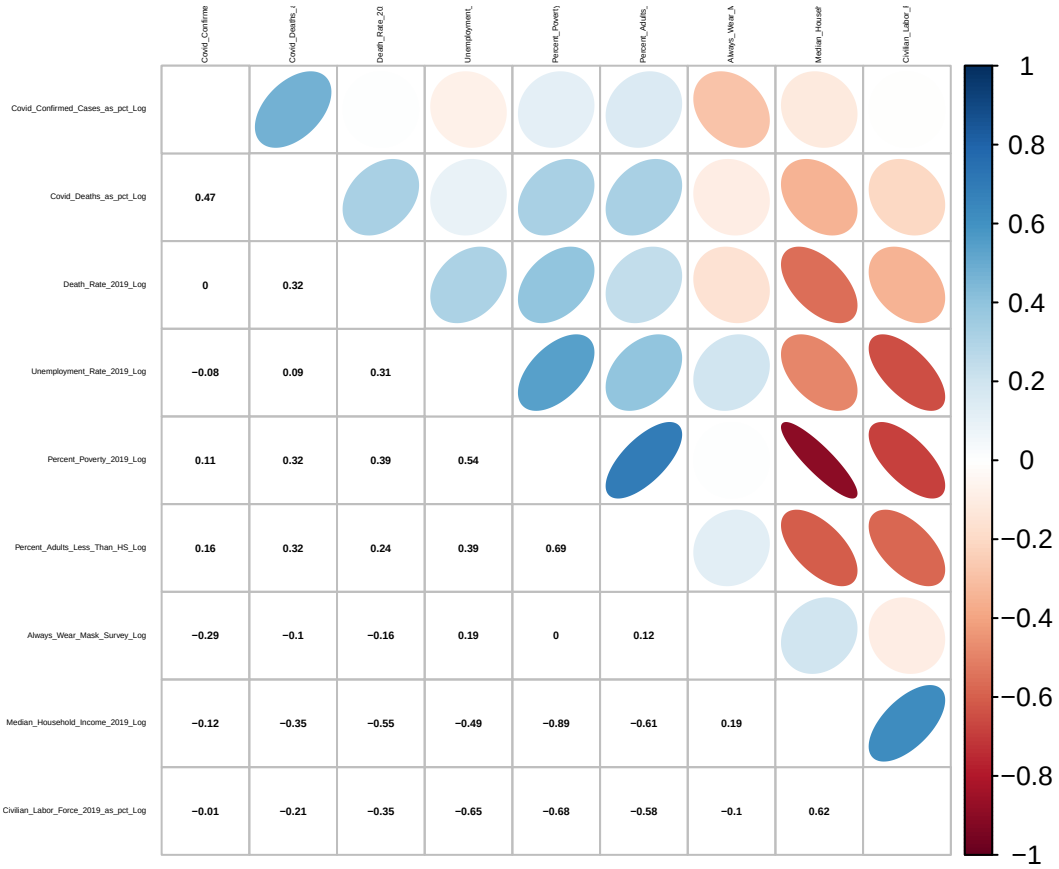
reduced the number of counties that we will analyze to 2,814 observation. Hence, outlier exclusion reduced the dataset by approximately 10%. This percent excluded is relatively substantial; however, we deemed the benefits of having univariate distributions outweighed this disadvantage. With these changes made, the 9 continuous variables all had univariate normal distributions.

Lack of Multivariate Normality



A chi-square quantile plot (shown above) reflects that our data does not have a multivariate normal distribution. Thus, we will ensure to deploy techniques that do not assume multivariate normality.

Variable Correlation



We note many variables highly correlated with other variables, which is appropriate for PCA. For instance, the correlation between the log of the unemployment rate and the labor force as a percent is -.065, the correlation between the log of the median household income and percent poverty is -0.88, and the correlation between the percent of COVID-19 cases and the percent of COVID-19 deaths is 0.47. There appear to be underlying trends about the counties (about beliefs about COVID-19, about wealth/education, etc) that could be summarized in linear combinations of the 19 metric variables we have currently.

Summary Statistics

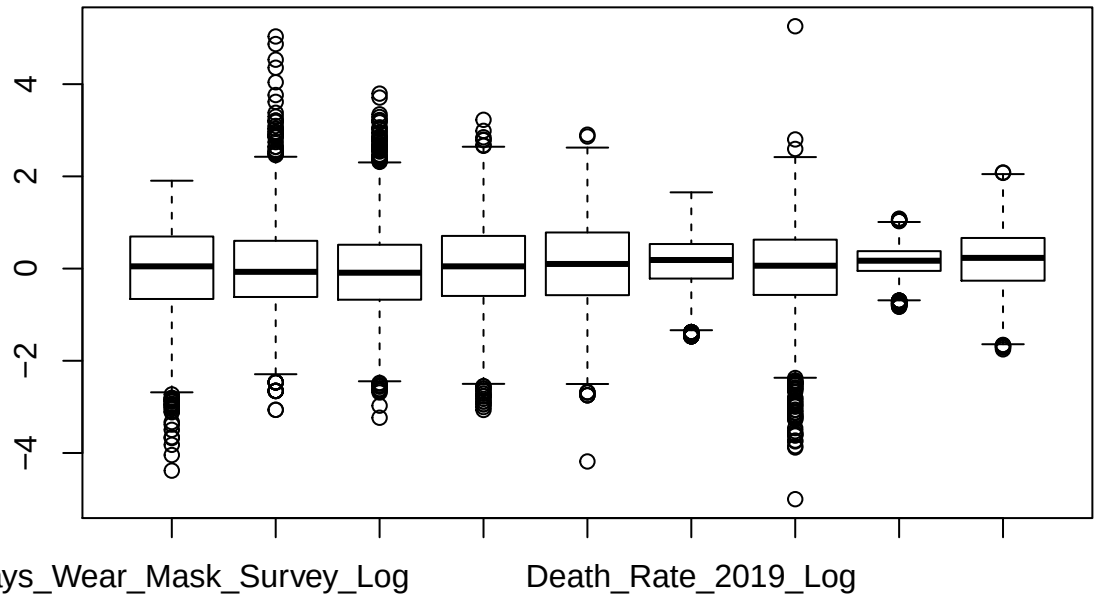
```
## [1] 2814   15
```

```
##
##    Rural Suburban    Urban
##      907      841     1066
```

```
##
##    0    1    2    3    4    5
## 1146  392  196  480  351  249
```

```
##  Economic_Typology_2015 Always_Wear_Mask_Survey_Log Unemployment_Rate_2019_Log
##  Min.   :0.000          Min.   :-4.38292           Min.   :-3.06445
##  1st Qu.:0.000          1st Qu.:-0.65971           1st Qu.:-0.61644
##  Median :1.000          Median : 0.04834           Median :-0.07051
##  Mean   :1.732          Mean   :-0.02779           Mean   : 0.01558
##  3rd Qu.:3.000          3rd Qu.: 0.69544           3rd Qu.: 0.60164
##  Max.   :5.000          Max.   : 1.90553           Max.   : 5.03446
##  Median_Household_Income_2019_Log Percent_Poverty_2019_Log
##  Min.   :-3.23567                 Min.   :-3.06671
##  1st Qu.:-0.67529                 1st Qu.:-0.59390
```

```
##  Median :-0.09013                 Median : 0.04824
##  Mean   :-0.05574                 Mean   : 0.04623
##  3rd Qu.: 0.51653                 3rd Qu.: 0.70815
##  Max.   : 3.79491                 Max.   : 3.22673
##  Percent_Adults_Less_Than_HS_Log Death_Rate_2019_Log
##  Min.   :-4.18428                Min.   :-1.4689
##  1st Qu.:-0.57692                1st Qu.:-0.2168
##  Median : 0.09978                Median : 0.1861
##  Mean   : 0.07065                Mean   : 0.1237
##  3rd Qu.: 0.78307                3rd Qu.: 0.5328
##  Max.   : 2.90401                Max.   : 1.6538
##  Civilian_Labor_Force_2019_as_pct_Log Covid_Confirmed_Cases_as_pct_Log
##  Min.   :-5.00174                     Min.   :-0.82906
##  1st Qu.:-0.57127                     1st Qu.:-0.05023
##  Median : 0.06175                     Median : 0.17048
##  Mean   :-0.03923                     Mean   : 0.15011
##  3rd Qu.: 0.62656                     3rd Qu.: 0.37812
##  Max.   : 5.25580                     Max.   : 1.08067
##  Covid_Deaths_as_pct_Log
##  Min.   :-1.7523
##  1st Qu.:-0.2623
##  Median : 0.2318
##  Mean   : 0.1925
##  3rd Qu.: 0.6637
##  Max.   : 2.0837
```



From the 2,814 US counties that we are analyzing, there is a fairly equitable distribution of rural-urban type: 907 rural, 841 suburban, and 1066 urban. The distributions in the quantitative variables are consistent, as we expected considering our previous standardization operation of continuous variables.

Principle Component Analysis

We use PCA to reduce the dimensionality of our dataset to find composite variables that are linear combinations of our metric variables. Note that the multivariate normality and variable correlations were already assessed in the "Descriptive Plot and Summary Statistics" section and determined to be suitable for PCA,

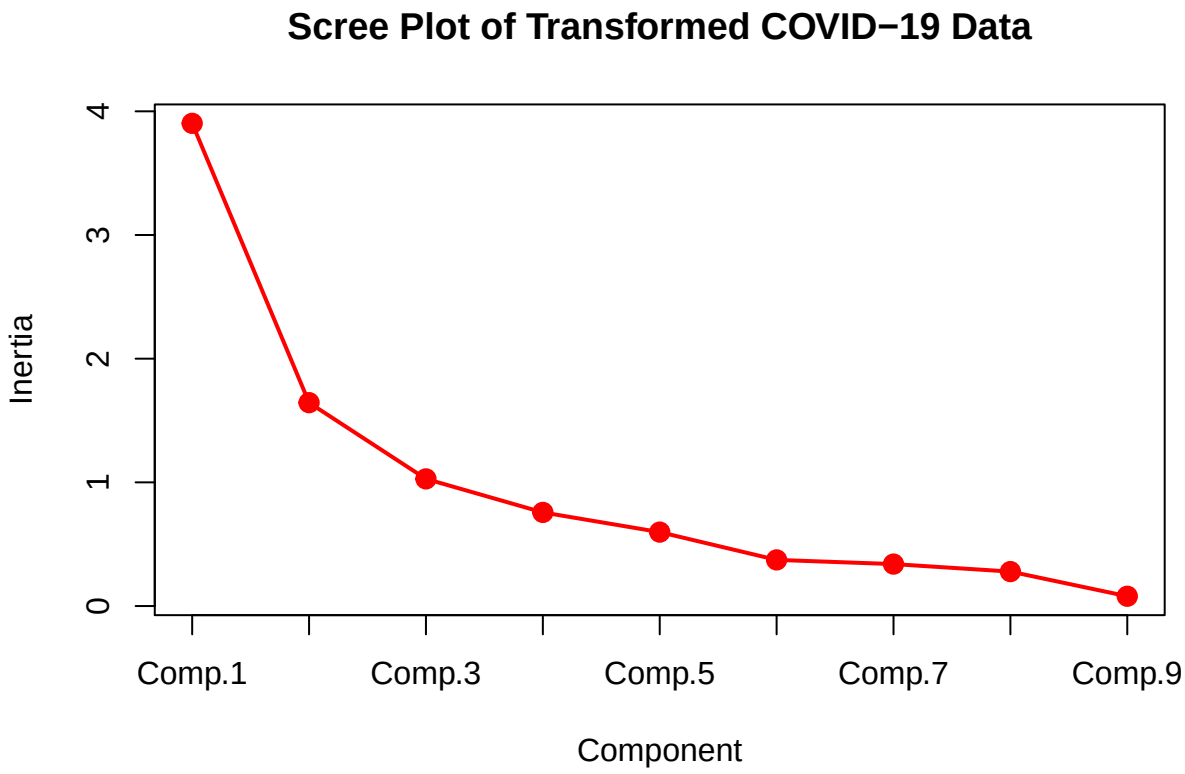
though parallel analysis may not be used due to the lack of multivariate normality.

```
## Importance of components:
##                           Comp.1    Comp.2    Comp.3     Comp.4     Comp.5
## Standard deviation     1.9755479 1.2823031 1.0139924 0.87008610 0.77310275
## Proportion of Variance 0.4336433 0.1827002 0.1142423 0.08411665 0.06640976
## Cumulative Proportion  0.4336433 0.6163434 0.7305857 0.81470236 0.88111212
##                            Comp.6     Comp.7     Comp.8      Comp.9
## Standard deviation     0.61072705 0.58241257 0.52776316 0.281540505
## Proportion of Variance 0.04144306 0.03768938 0.03094822 0.008807228
## Cumulative Proportion  0.92255518 0.96024455 0.99119277 1.000000000
```

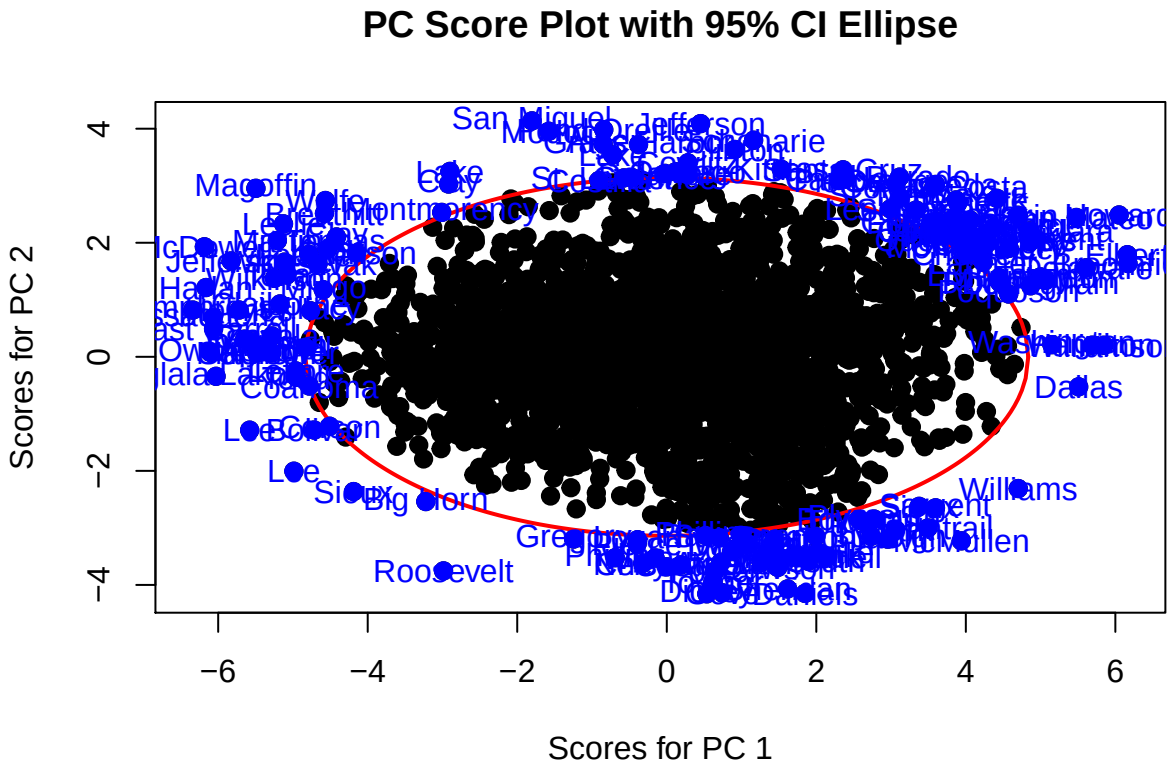
```
## Warning in if (loadings) {: the condition has length > 1 and only the first
## element will be used
```

```
##
## Loadings:
##                                    Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6
## Always_Wear_Mask_Survey_Log         0.01   0.52   0.57   0.45   0.11   0.25
## Unemployment_Rate_2019_Log         -0.34   0.32  -0.01   0.02  -0.70  -0.07
## Median_Household_Income_2019_Log    0.45   0.07   0.21   0.14  -0.21   0.03
## Percent_Poverty_2019_Log           -0.46   0.04   0.01  -0.22   0.22  -0.07
## Percent_Adults_Less_Than_HS_Log    -0.39   0.04   0.32  -0.20   0.44   0.23
## Death_Rate_2019_Log                -0.29  -0.11  -0.51   0.62   0.03   0.47
## Civilian_Labor_Force_2019_as_pct_Log  0.41  -0.20  -0.04   0.13   0.27   0.14
## Covid_Confirmed_Cases_as_pct_Log   -0.09  -0.60   0.40  -0.16  -0.38   0.52
## Covid_Deaths_as_pct_Log            -0.23  -0.46   0.31   0.52   0.02  -0.60
##                                    Comp.7 Comp.8 Comp.9
## Always_Wear_Mask_Survey_Log         0.25   0.21   0.12
## Unemployment_Rate_2019_Log          0.15  -0.51   0.00
## Median_Household_Income_2019_Log   -0.41  -0.10  -0.71
## Percent_Poverty_2019_Log            0.45   0.16  -0.68
## Percent_Adults_Less_Than_HS_Log    -0.46  -0.50   0.02
## Death_Rate_2019_Log                -0.14   0.01  -0.14
## Civilian_Labor_Force_2019_as_pct_Log  0.54  -0.62  -0.05
## Covid_Confirmed_Cases_as_pct_Log    0.12   0.14   0.02
## Covid_Deaths_as_pct_Log            -0.04  -0.08   0.00
```

```
## Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8 Comp.9
##   3.90   1.64   1.03   0.76   0.60   0.37   0.34   0.28   0.08
```



Deciding how many PC's to keep: According to the total variance explained method, using a cutoff of 1, the first 3 PC's should be used. According to the Eigenvalue > 1 method, the first 3 PC's should be used. According to the scree plot elbow method, the first 1 PC's should be used. We choose to maintain the first 3 PC's in accordance with the first two methods for a parsimonous but still informative model.



There are no noticeable trends or outliers on the score plot, which is good.

```
## Importance of components:
##                           Comp.1    Comp.2    Comp.3     Comp.4     Comp.5
## Standard deviation     1.9755479 1.2823031 1.0139924 0.87008610 0.77310275
## Proportion of Variance 0.4336433 0.1827002 0.1142423 0.08411665 0.06640976
## Cumulative Proportion  0.4336433 0.6163434 0.7305857 0.81470236 0.88111212
##                            Comp.6     Comp.7     Comp.8      Comp.9
## Standard deviation     0.61072705 0.58241257 0.52776316 0.281540505
## Proportion of Variance 0.04144306 0.03768938 0.03094822 0.008807228
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```
##
## Loadings:
##                                    Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6
## Always_Wear_Mask_Survey_Log         0.01   0.52   0.57   0.45   0.11   0.25
## Unemployment_Rate_2019_Log         -0.34   0.32  -0.01   0.02  -0.70  -0.07
## Median_Household_Income_2019_Log    0.45   0.07   0.21   0.14  -0.21   0.03
## Percent_Poverty_2019_Log           -0.46   0.04   0.01  -0.22   0.22  -0.07
## Percent_Adults_Less_Than_HS_Log    -0.39   0.04   0.32  -0.20   0.44   0.23
## Death_Rate_2019_Log                -0.29  -0.11  -0.51   0.62   0.03   0.47
## Civilian_Labor_Force_2019_as_pct_Log  0.41  -0.20  -0.04   0.13   0.27   0.14
## Covid_Confirmed_Cases_as_pct_Log   -0.09  -0.60   0.40  -0.16  -0.38   0.52
## Covid_Deaths_as_pct_Log            -0.23  -0.46   0.31   0.52   0.02  -0.60
##                                    Comp.7 Comp.8 Comp.9
## Always_Wear_Mask_Survey_Log         0.25   0.21   0.12
## Unemployment_Rate_2019_Log          0.15  -0.51   0.00
## Median_Household_Income_2019_Log   -0.41  -0.10  -0.71
## Percent_Poverty_2019_Log            0.45   0.16  -0.68
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## Civilian_Labor_Force_2019_as_pct_Log  0.54  -0.62  -0.05
## Covid_Confirmed_Cases_as_pct_Log    0.12   0.14   0.02
## Covid_Deaths_as_pct_Log            -0.04  -0.08   0.00
```

Looking at PC1: This principle component seems to be related to wealth, employment status, and education. It combines log percent poverty (-0.46) with the log of the median household income (0.45), the log of the civilian labor force (0.41), and the percent of adults with a bachelor's degree or higher (-0.39). A higher value on this PC indicates more employment, more jobs, and more education.

Looking at PC2: This principle component seems to be a measure of masking behaviors and relation to COVID-19 infection. It combines the percentage of those who say they always mask (0.52), the log of the COVID-19 infection rate (-0.60), and the log of the COVID-19 death rate (-0.46). A higher value on this PC indicates more masking and less COVID-19 infection and death.

Looking at PC3: This principle component seems to be a combination of the first two and relates underlying traits about the county to COVID-19 infection. It combines the log of the 2019 death rate (-0.51) with the cumulative percentage of population with the log of the percentage of adults with less than a high school degree (0.32), the log of the COVID-19 infection rate (0.40), and the log of the COVID-19 death rate (0.31). A higher value on this PC indicates less education and more COVID-19 infection and death.

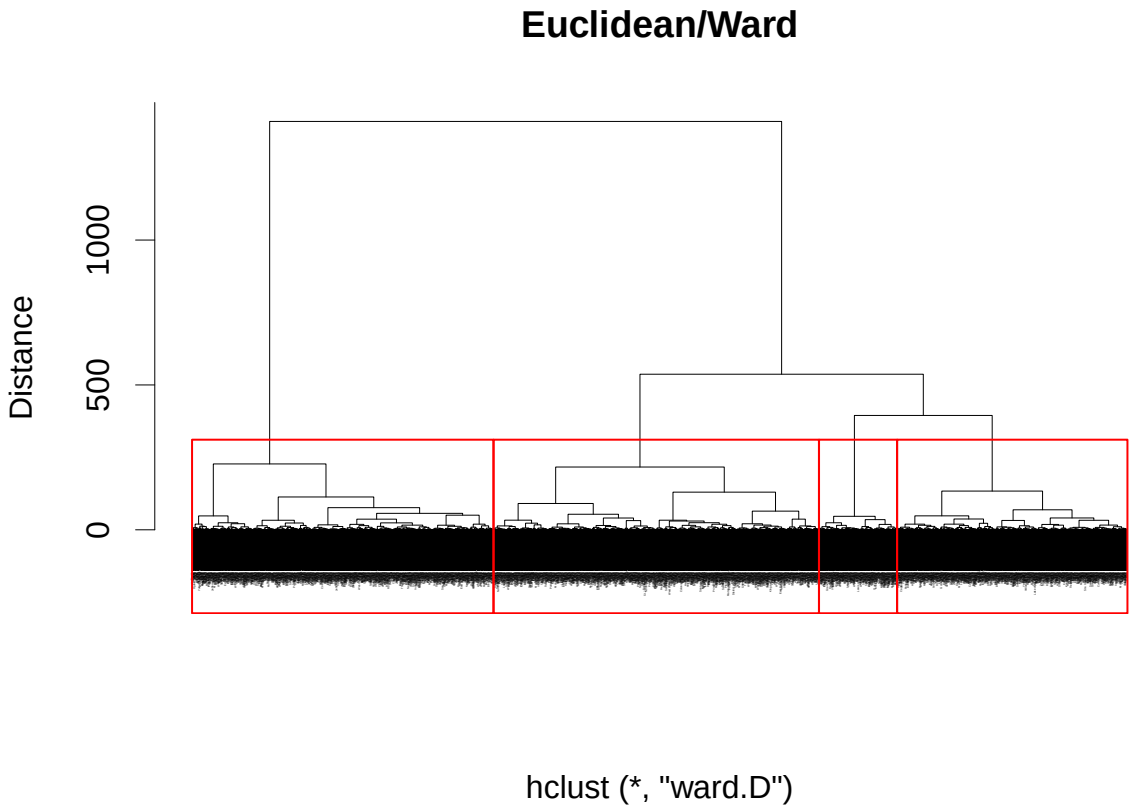
Using PCA, we can reduce 9 metric variables to 3 composite variables that are related to wealth and education, attitudes about masking, and population. These 3 PC's can account for 73% of the total variability. We note that COVID-19 infection and death rates are related to attitudes and behaviors, like the masking rate,

but are also due to factors outside of the control of a county's population, like unemployment and education.

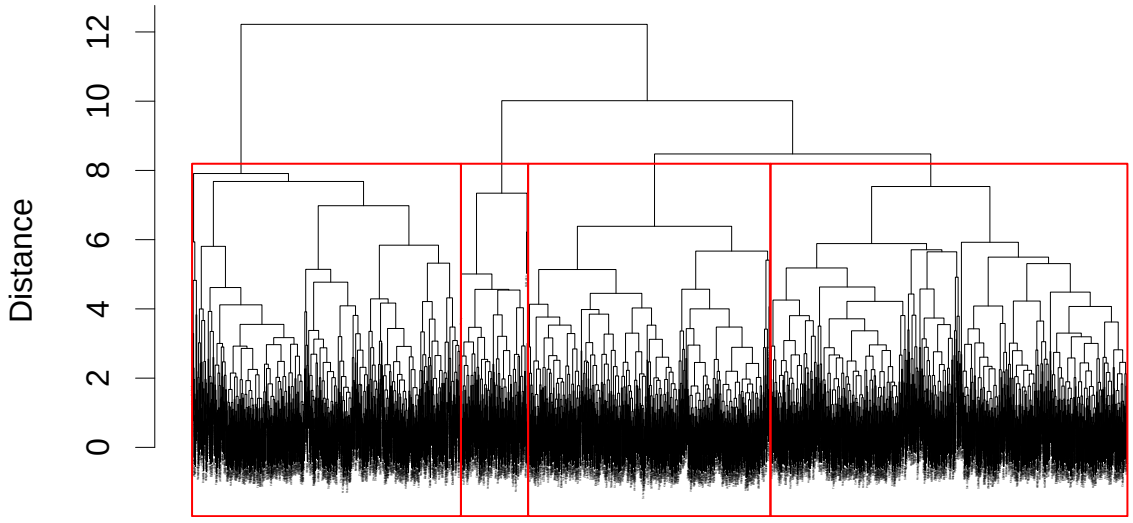
Cluster Analysis

We use cluster analysis to find groups of counties that are similar to each other but different from other counties across our metric variables. We are finding clusters of *observations*, unlike in PCA where we found clusters of *variables.*

Our first task is to determine a distance and agglomeration method; we compare Euclidean versus Chebychev for distance and Ward versus complete for agglomeration. We choose a k value of 4 as has been indicated by our past pset work but will further explore cluster sizes after determining our preferred methods.

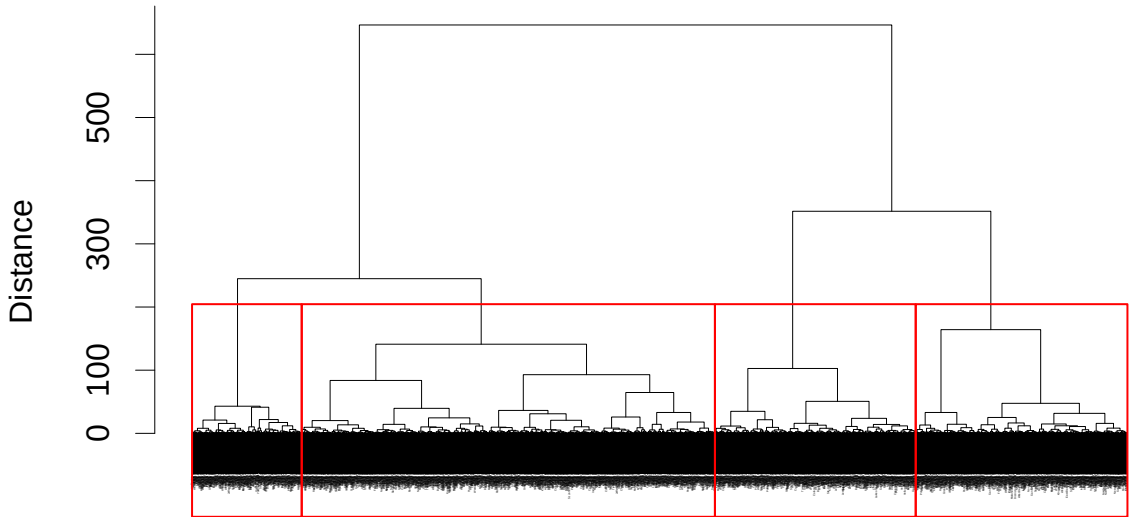


Euclidean/Complete

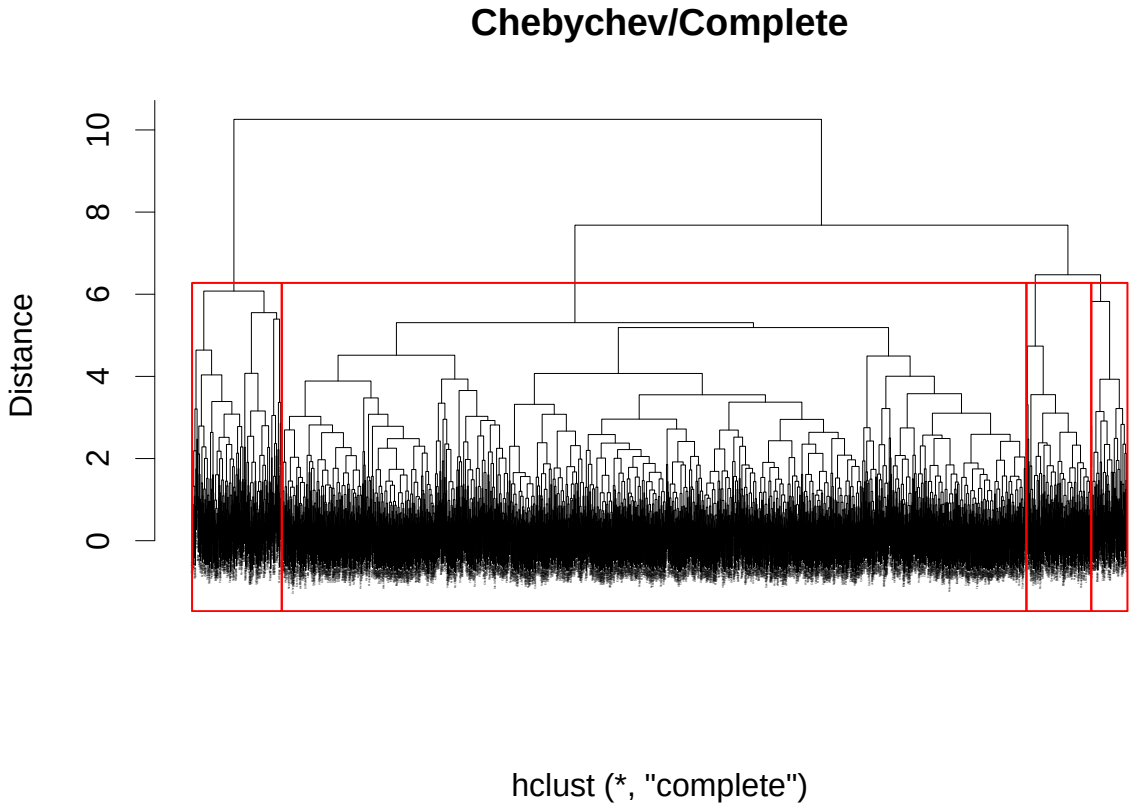


hclust (*, "complete")

Chebychev/Ward



hclust (*, "ward.D")

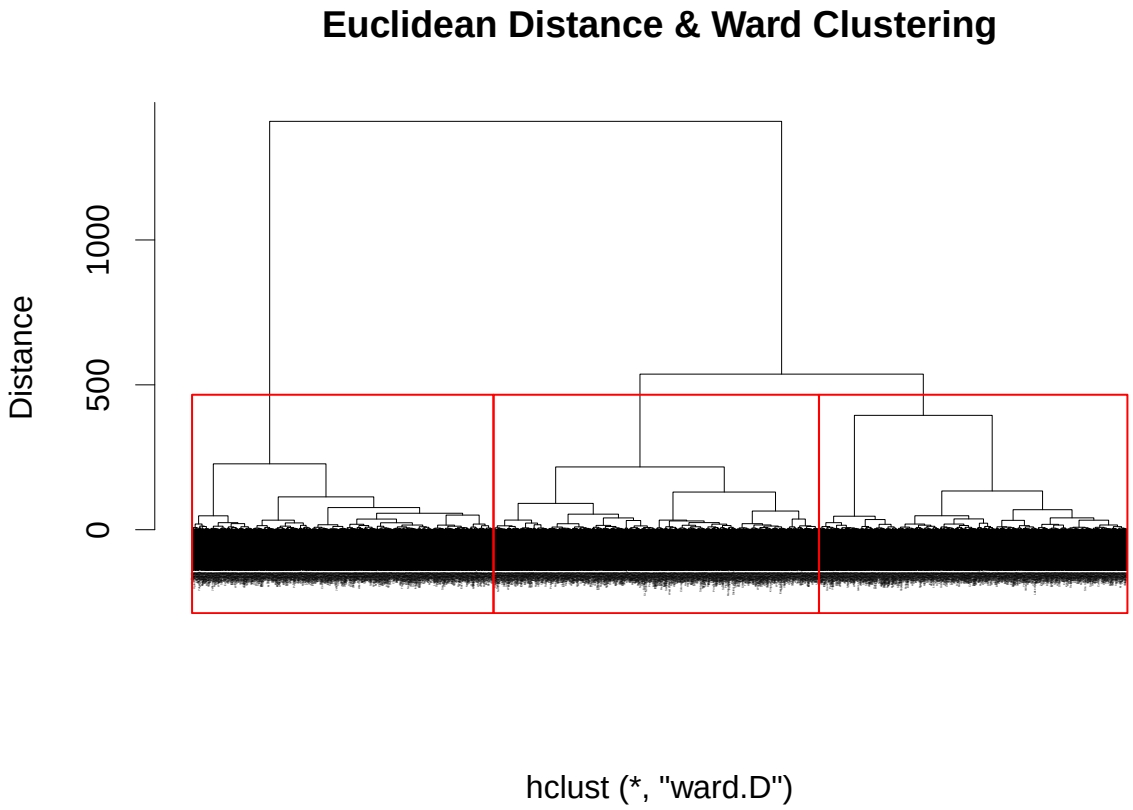


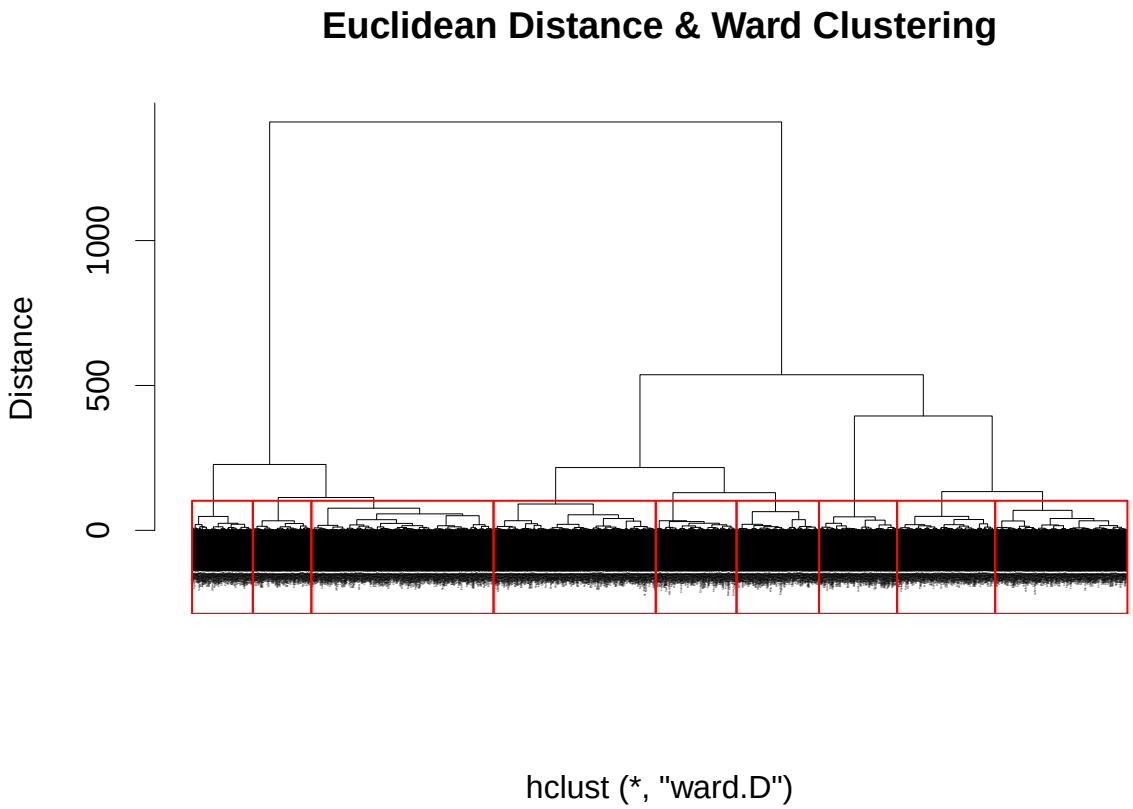
Explanation of agglomeration method: It's clear that the Ward's method gives much neater groupings than the complete linkage method. That is, the complete linkage clusters become very granular at much higher distances. It looks like Ward's might be the way to go, at least for these data.

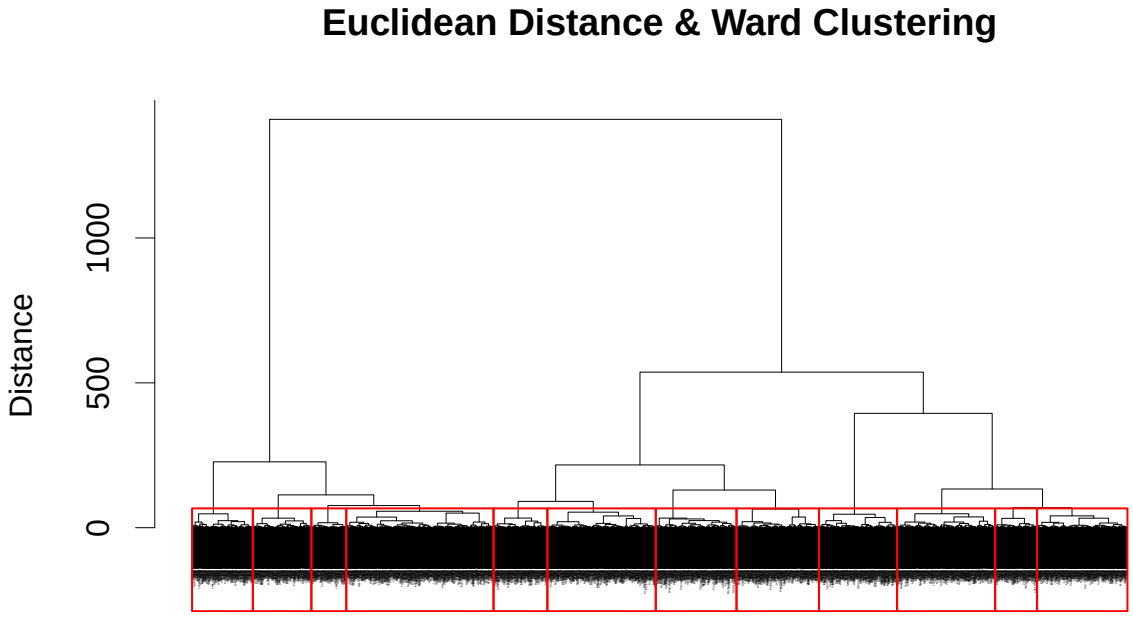
Explanation of distance method: The distance methods are both Minowskis with very different exponents: Euclidean and a Chebychev approximation. It seems that Euclidean/Ward gives the cleanest, most sensible clusters, so we choose this combination moving forward.

Our next goal is to determine how many clusters would be appropriate with our Euclidean/Ward technique.

There are peaks in the RMSSTD at 3, 9, and most notably 12,indicating that these may be reasonable group counts. SPRSQ tapers at 9, supporting the idea that there may be 9 groups. However, the tapering is far more prominent at 2 and 4 and is echoed in the RSQ, so a lower group count may be indicated. Below, we examine the fits for 3, 9, and 12 clusters using dendograms and cluster plots in both principle component space.


Euclidean Distance & Ward Clustering
Distance
0
500
1000
hclust (*, "ward.D")


Euclidean Distance & Ward Clustering
Distance
0
500
1000
hclust (*, "ward.D")


Euclidean Distance & Ward Clustering
Distance
0
500
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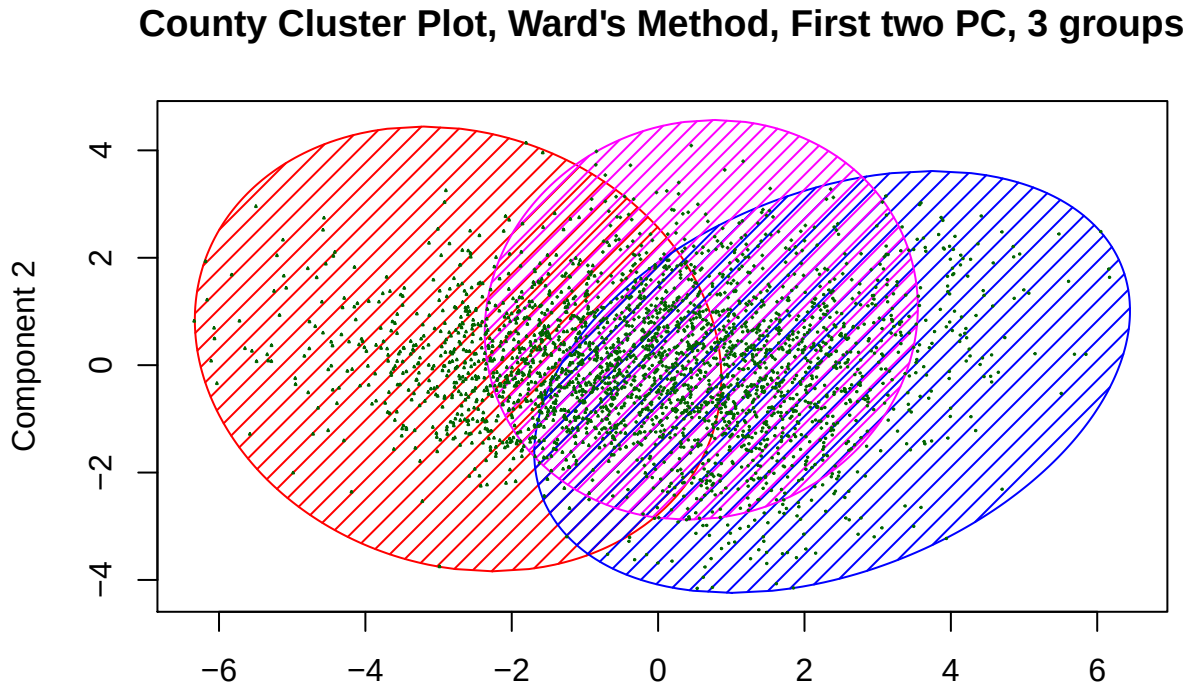
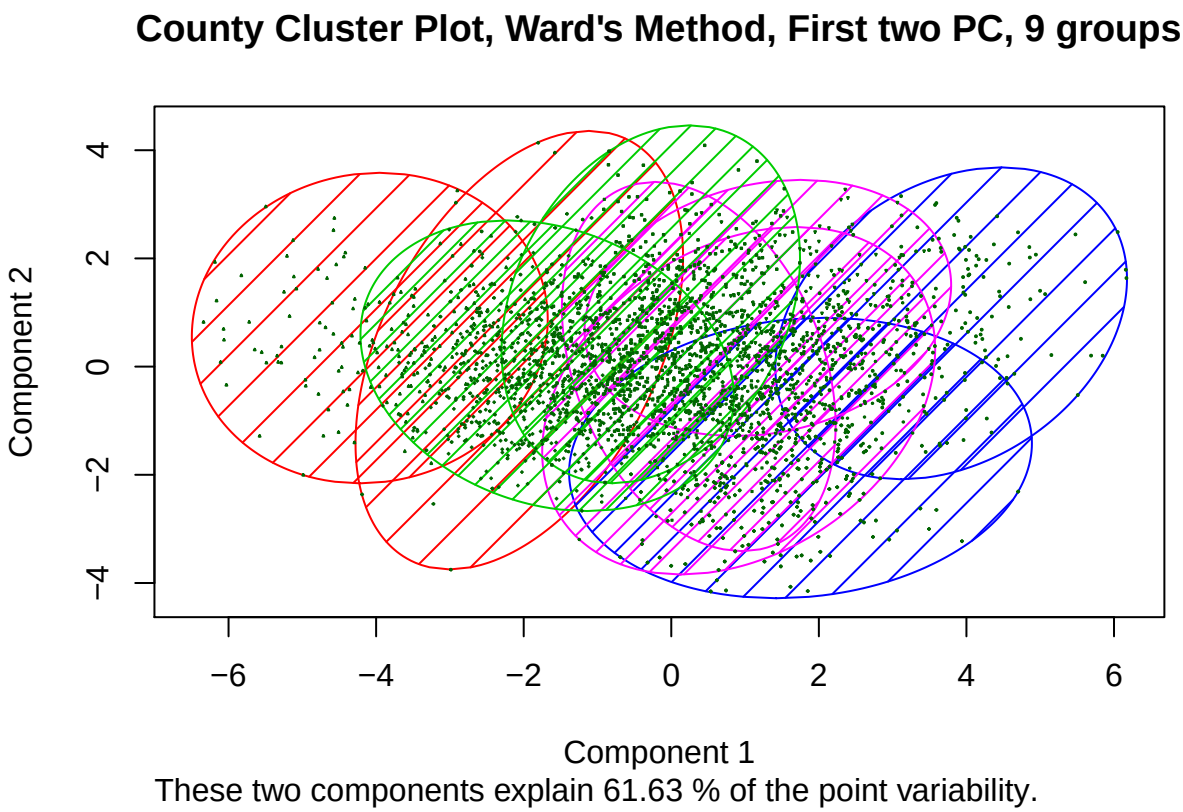
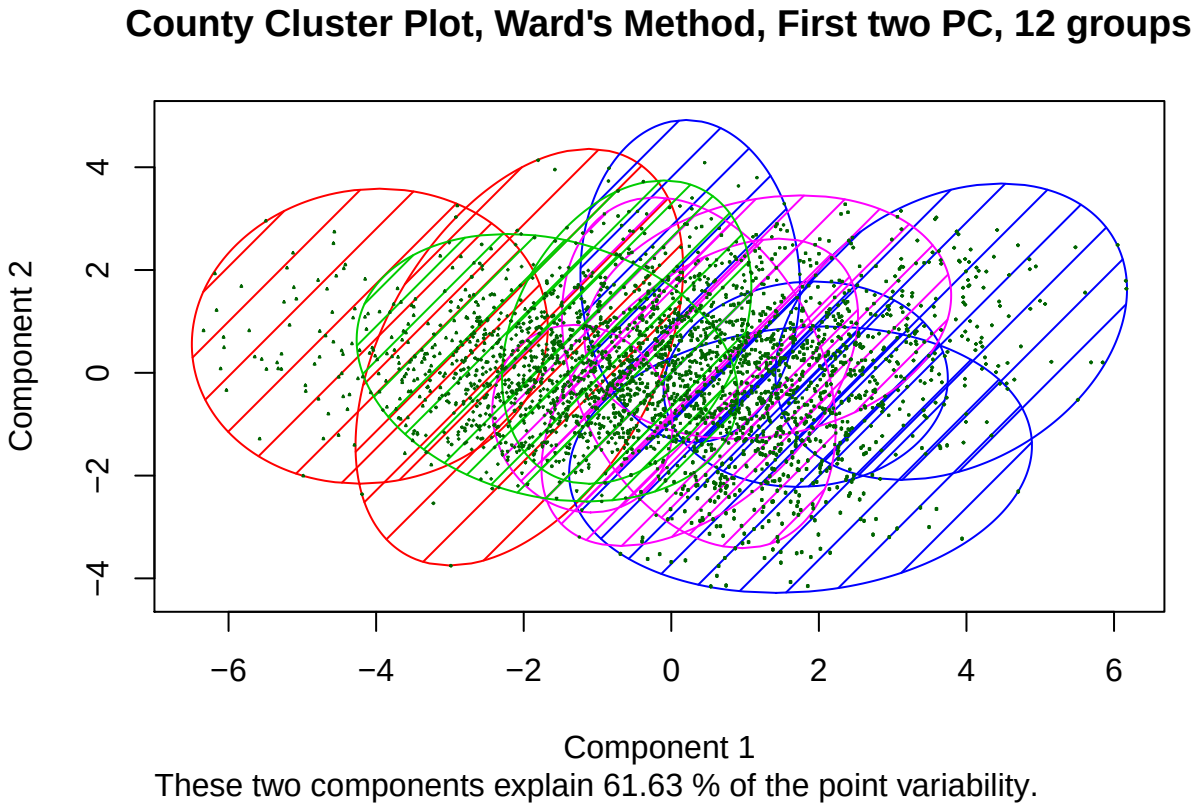
hclust (*, "ward.D")


County Cluster Plot, Ward's Method, First two PC, 3 groups
Component 2
−4
−2
0
2
4
−6
−4
−2
0
2
4
6
Component 1
These two components explain 61.63 % of the point variability.





The large spike in RMSSTD is very promising for the largest cluster size of 12, and the dendrogram clustering looks apt as well, but we don't want to run the risk of having too many clusters. For the most parsimonous

model, we examine 3 clusters that primarily differ on their wealth/education/employment and COVID-19 infection and death rates.

```
##   Group.1 Always_Wear_Mask_Survey_Log Unemployment_Rate_2019_Log
## 1       1                  0.74326479                 -0.2676882
## 2       2                 -1.05432737                 -0.6549327
## 3       3                  0.06360357                  0.6206986
##   Median_Household_Income_2019_Log Percent_Poverty_2019_Log
## 1                        0.8737143               -0.7273323
## 2                        0.1357098               -0.4015587
## 3                       -0.8166837                0.8554088
##   Percent_Adults_Less_Than_HS_Log Death_Rate_2019_Log
## 1                      -0.4726441         -0.21062228
## 2                      -0.4377790          0.08332214
## 3                       0.7571856          0.38009164
##   Civilian_Labor_Force_2019_as_pct_Log Covid_Confirmed_Cases_as_pct_Log
## 1                            0.4384405                       0.01800456
## 2                            0.6435415                       0.26990946
## 3                           -0.7865695                       0.16862940
##   Covid_Deaths_as_pct_Log
## 1              -0.1854335
## 2               0.2383466
## 3               0.4264292
```

Clusters 1 and 3 are relatively well-off economically. Both have high household incomes, low poverty rates, high civilian labor forces, low unemployment rates, and high education rates. Cluster 3 is more well-off than Cluster 1, perhaps representing those with higher paying jobs. The biggest difference, though, is in COVID-19 responses. Cluster 1 has high COVID-19 infection (0.53) and death rates (0.22), while Cluster 3 has low COVID-19 infection (-0.60) and death rates (-0.75). This difference can potentially be tied back to behavioral differences: counties in Cluster 3 always mask (0.68) while counties in Cluster 1 do not (-0.88). It is important to note that this difference is not necessarily due to any sort of moral gap but more likely due to a gap in resources - it is a privilege to be able to stay informed on scientific discoveries, purchase masks, and maintain social distancing. We only note connections but cannot specify any causal relationships.

In contrast to Clusters 1 and 3, Cluster 2 is underprivileged, with low household income (-0.82), high poverty (0.85), low civilian labor force (-0.82), and a high percent with less than a high school degree (0.76). Cluster 2 is hit the hardest by COVID-19, with the highest death rate (0.42). Here we most clearly see the connection between underlying economic factors and the impact of COVID-19. Members of these communities may have jobs as essential workers that require work outside of the home. They may have to take public transit. They may be unable to afford grocery delivery services. Affluent communities have the resources to avoid COVID-19 transmission, while impoverished communities may not. These communities are likely to have preexisting conditions that worsen the effects of COVID-19 and may lack quality healthcare or health insurance. We also note a potential gap in testing in these communities - death rates are high, but the reported infection rate is low (-0.01). As we continue to distribute COVID-19 vaccinations, special attention should be placed on supporting these communities most at risk for severe negative consequences associated with COVID-19.

Ordination

With ordination, we are seeking to answer the question: Which U.S. states are similar to one another? Our ordination strategies deployed (i.e., CA, DCA, NMDS) are similar to PCA, but analyze *relative* values. PCA decomposes relations between columns only, whereas correspondence analysis decomposes rows as well. Moreover, with our ordination techniques, we are seeking to explore the distribution of *states* with respect to these pertinent socioeconomic and COVID-19 variables. In this part of the report, we analyze aggregate statistics by state, i.e., taking means of continuous variables for all counties in each state. Organizing by the 50 states + D.C. will allow for more insightful visualizations to bolster our analysis.

Of our original 9 continuous variables, we assign 5 continuous variables for correspondence analysis: Always_Wear_Mask_Survey, Median_Household_Income_2019, Percent_Poverty_2019, Percent_Adults_Less_Than_HS, and Covid_Confirmed_Cases_as_pct.

For additional continuous variables, we make an environmental dataset. We look at four additional continuous variables describing each state: Unemployment_Rate_2019, Death_Rate_2019, Civilian_Labor_Force_2019_as_pct, and Covid_Deaths_as_pct.

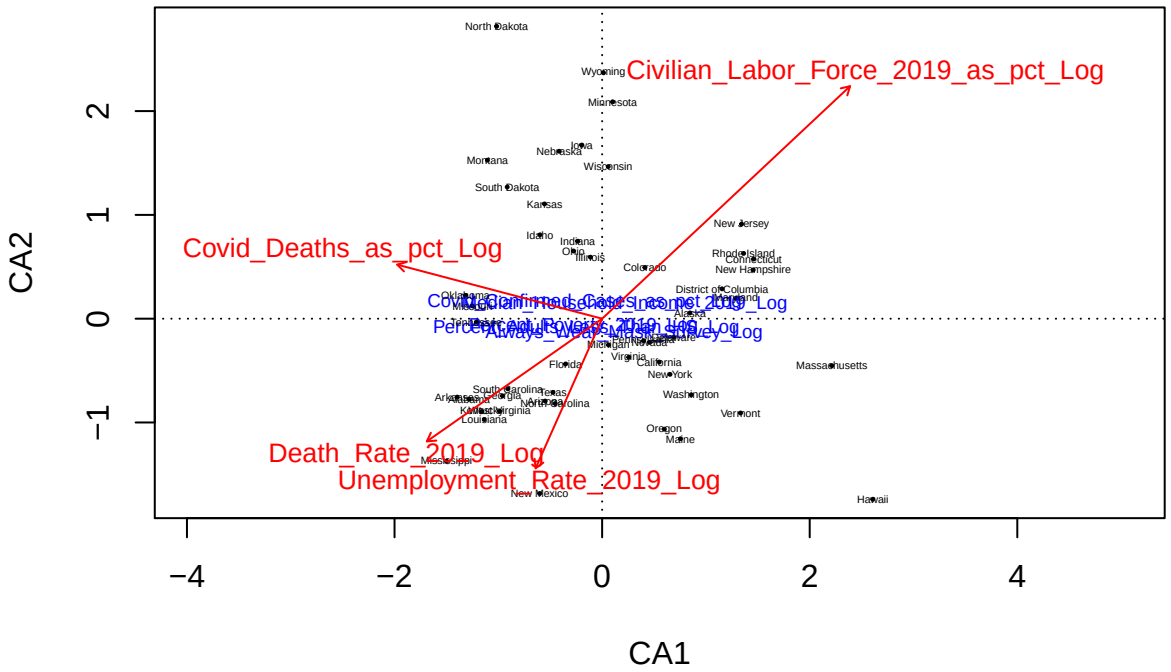
We first applied correspondence analysis. Because correspondence analysis (CA) requires continuous variables to take on positive values, we applied a +2.5 pseudoshift to all values.

```
##
## Call:
## cca(X = stlm_CA_cont)
##
## Partitioning of scaled Chi-square:
##               Inertia Proportion
## Total         0.05682          1
## Unconstrained 0.05682          1
##
## Eigenvalues, and their contribution to the scaled Chi-square
##
## Importance of components:
##                            CA1     CA2      CA3      CA4
## Eigenvalue            0.03582 0.01599 0.003596 0.001413
## Proportion Explained  0.63041 0.28144 0.063289 0.024862
## Cumulative Proportion 0.63041 0.91185 0.975138 1.000000
##
## Scaling 2 for species and site scores
## * Species are scaled proportional to eigenvalues
## * Sites are unscaled: weighted dispersion equal on all dimensions
##
##
## Species scores
##
##                                     CA1      CA2      CA3      CA4
## Always_Wear_Mask_Survey_Log       0.2121 -0.13953 -0.05716 -0.01682
## Median_Household_Income_2019_Log  0.2168  0.13882  0.05778  0.01296
## Percent_Poverty_2019_Log         -0.1792 -0.07444  0.07265 -0.04758
## Percent_Adults_Less_Than_HS_Log  -0.1520 -0.09037  0.00511  0.06782
## Covid_Confirmed_Cases_as_pct_Log -0.1686  0.16179 -0.07793 -0.01438
##
##
## Site scores (weighted averages of species scores)
##
##                            CA1      CA2      CA3        CA4
## Alabama              -1.28139 -0.77464  0.02819  0.5159842
## Alaska                0.84657  0.05548  3.42947  0.6867029
## Arizona              -0.54854 -0.79361 -0.91355 -0.6991435
## Arkansas             -1.39634 -0.75539 -0.03808 -0.3100598
## California            0.55030 -0.41748 -0.02561  1.5472187
## Colorado              0.41252  0.49312 -0.21475 -2.0320027
## Connecticut           1.46117  0.57525 -1.31532 -0.1026698
## Delaware              0.69141 -0.17728 -1.55442 -0.4474717
## District of Columbia  1.15524  0.28741  1.42909 -1.0908641
```

```
## Florida             -0.35199 -0.43635 -0.54863  0.1206408
## Georgia             -0.96075 -0.74328  0.02916  0.8142786
## Hawaii               2.60861 -1.73961  3.12142  0.6723731
## Idaho               -0.59868  0.80770  0.65136  0.7312862
## Illinois            -0.11231  0.59270 -0.72768 -0.3053003
## Indiana             -0.23494  0.74656 -0.52631  1.7085238
## Iowa                -0.19606  1.67274 -0.24293 -0.6496432
## Kansas              -0.55454  1.10549 -0.14013 -0.3704389
## Kentucky            -1.15773 -0.89474  0.20784  0.7492116
## Louisiana           -1.13467 -0.97141  0.35872 -0.1173177
## Maine                0.75512 -1.15683  0.95829 -1.8481374
## Maryland             1.28998  0.19824 -0.68758  0.9538218
## Massachusetts        2.21342 -0.45288  0.76958  0.5150260
## Michigan             0.06114 -0.25270 -0.76069 -1.9014572
## Minnesota            0.10096  2.08968 -0.03692  0.4194122
## Mississippi         -1.49852 -1.37356 -0.15480 -0.6132548
## Missouri            -1.24885  0.12303  0.92540  0.7603853
## Montana             -1.10499  1.52714  1.76296 -3.0877916
## Nebraska            -0.41390  1.61304  0.49411 -0.7363732
## Nevada               0.45630 -0.22800  0.13519  1.0057279
## New Hampshire        1.45612  0.46978 -0.61229 -0.0585913
## New Jersey           1.34343  0.91171 -1.48752  1.1629498
## New Mexico          -0.60119 -1.68412 -0.37097 -1.3776595
## New York             0.65417 -0.53623 -0.82335 -0.8287860
## North Carolina      -0.45167 -0.81779 -0.58293  0.2448985
## North Dakota        -1.01637  2.81649  1.59873  1.5639942
## Ohio                -0.27531  0.65207  0.18923  0.8573743
## Oklahoma            -1.31567  0.22479  0.57549  0.2103930
## Oregon               0.59937 -1.06456  0.78984 -0.1140676
## Pennsylvania         0.39958 -0.21195 -1.29148 -0.8281448
## Rhode Island         1.36373  0.62913 -1.82265 -0.0108070
## South Carolina      -0.90741 -0.67618 -0.35109 -0.0212616
## South Dakota        -0.91424  1.26839  0.21881 -1.0916075
## Tennessee           -1.21156 -0.03252 -0.12798  1.4174893
## Texas               -0.47309 -0.70956 -0.47961  1.7880818
## Vermont              1.33404 -0.90874  0.35915 -0.6961486
## Virginia             0.25708 -0.37160 -0.65079  1.0542256
## Washington           0.85862 -0.73396  0.54964 -0.3475639
## West Virginia       -0.98726 -0.89151  0.35889 -0.0005736
## Wisconsin            0.05925  1.46551 -0.64578 -0.5048848
## Wyoming              0.01334  2.36890  1.03710 -0.4521443
```

Discussion of inertia: Equal to squared eigenvalues, inertia is like variance and measures departures from the independence model. We see that the inertia value is 0.05682. The magnitude of inertia does not reflect more or less variance; it is reflective of the magnitude of the data, which in our case is limited by the data being shifted log values.

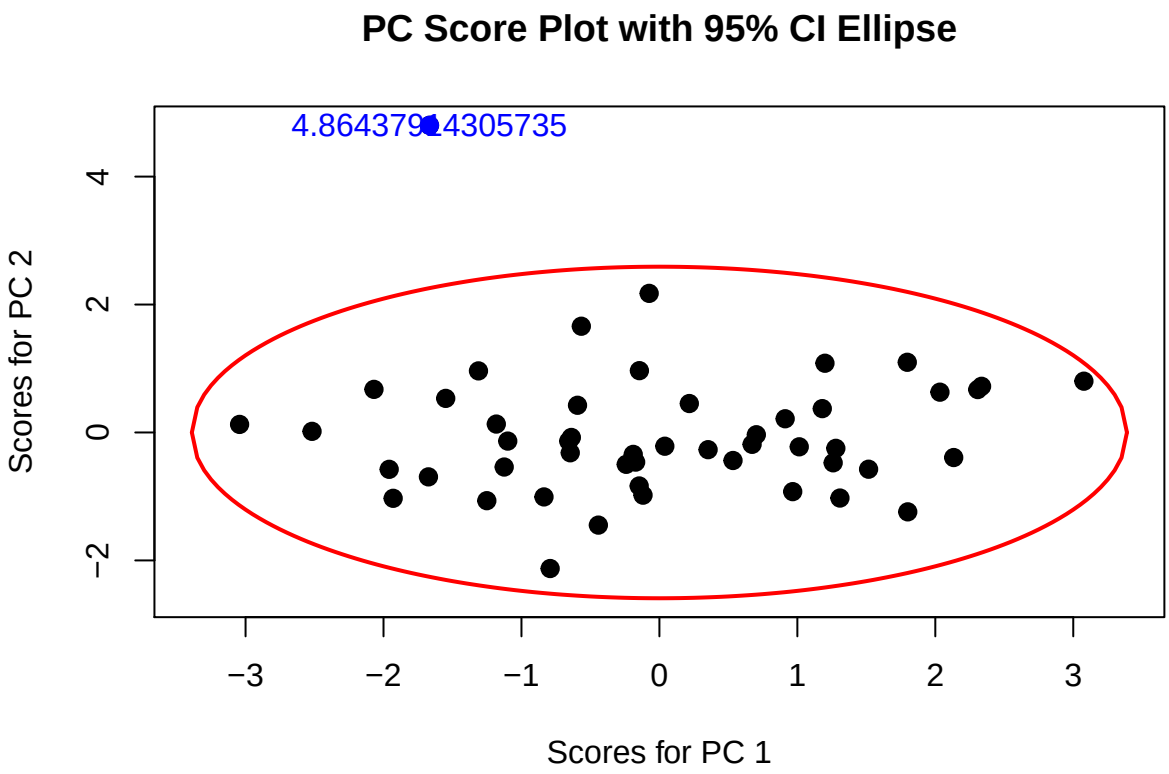
Deciding how many directions to keep: From the output data above in the "proportion explained" row, we can see that first CA direction explains ~63.0% of the relation. The "cumulative proportion" by the second CA direction is ~91.2%. Hence, the first two CA directions explain the vast majority of total inertia. The third and fourth directions have significantly smaller "proportion explained" values. This suggests that there are likely two major underlying discriminatory dimensions captured by the data of the 50 U.S. states (which reflect aggregate county data). To get a sense of these two CA directions, we subsequently plotted them overlaid with the aforementioned environmental variables.



We subsequently calculated p-values for the overlaid environmental variables, and found that the four overlaid environmental variables are all significant with $p<0.05$.

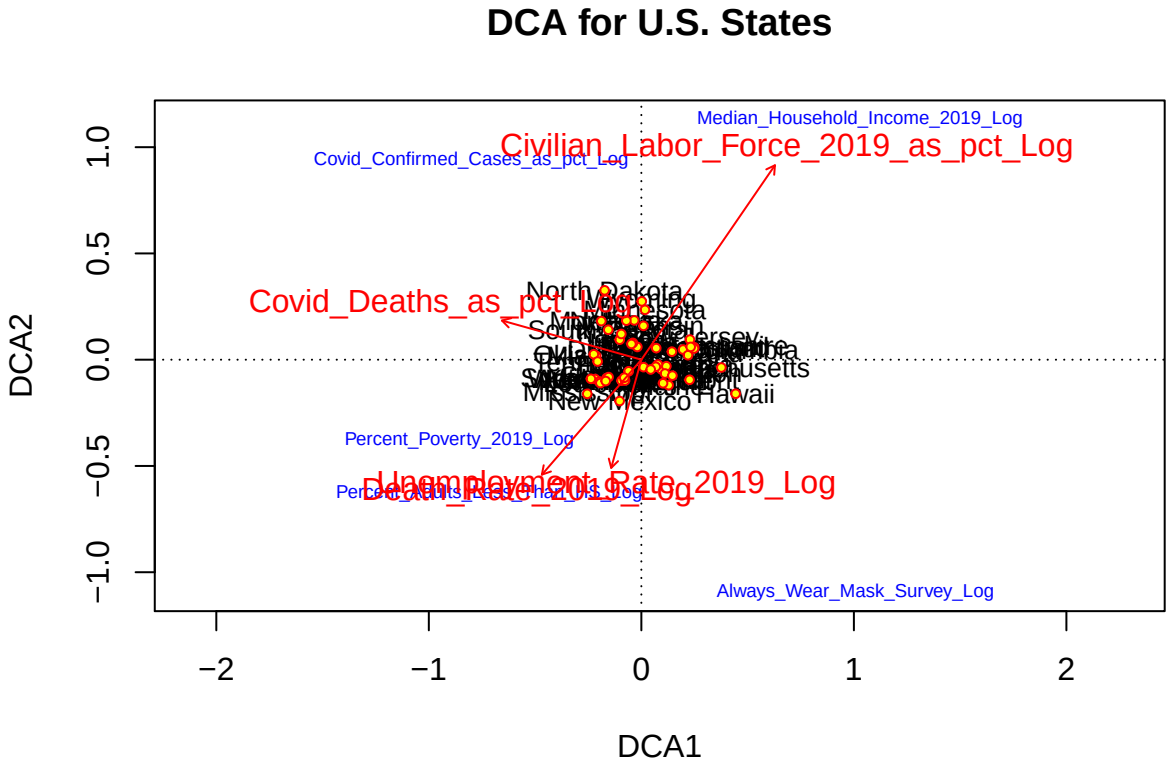
```
##
## ***VECTORS
##
##                                          CA1      CA2     r2   Pr(>r)
## Unemployment_Rate_2019_Log           -0.40625 -0.91376 0.1895 0.010989 *
## Death_Rate_2019_Log                  -0.81926 -0.57342 0.3237 0.000999 ***
## Civilian_Labor_Force_2019_as_pct_Log  0.72950  0.68398 0.8168 0.000999 ***
## Covid_Deaths_as_pct_Log              -0.96695  0.25497 0.3177 0.000999 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Permutation: free
## Number of permutations: 1000
```

From our first correspondence analysis plot including the first two CA directions, we are able to deduce the similarities and differences between states with respect to the applied continuous variables. Overall, the counties seem evenly and scattered between the four quadrants. Generally, higher values along the first CA direction are associated with higher civilian labor force participation, fewer COVID-19 cases/deaths, lower death rate, and lower unemployment. Higher values along the second CA direction are associated primarily with poor masking behaviors, greater COVID-19 cases/deaths, and greater unemployment. These results perhaps indicate two different types of counties that are associated with high COVID-19 rates (those in poorer, disadvantaged areas and also those with poor masking behaviors). This first CA direction explained the majority of the relation and is thus most pertinent. Interestingly, for the second CA direction higher civilian labor force participation is associated with slightly higher COVID-19 deaths. Although this could perhaps point to more workplace exposure to COVID-19, we see that the inverse relationship for civilian labor force + COVID-19 cases is conveyed from the first, and more significant, CA direction. Thus, it is likely they are negatively correlated.



From the above, we can see that there is no evidence of data snaking in higher dimensional space. Evidence of snaking would be a PCA score plot that looks like a horseshoe. However, the above scoreplot appears random and therefore does not indicate data snaking.

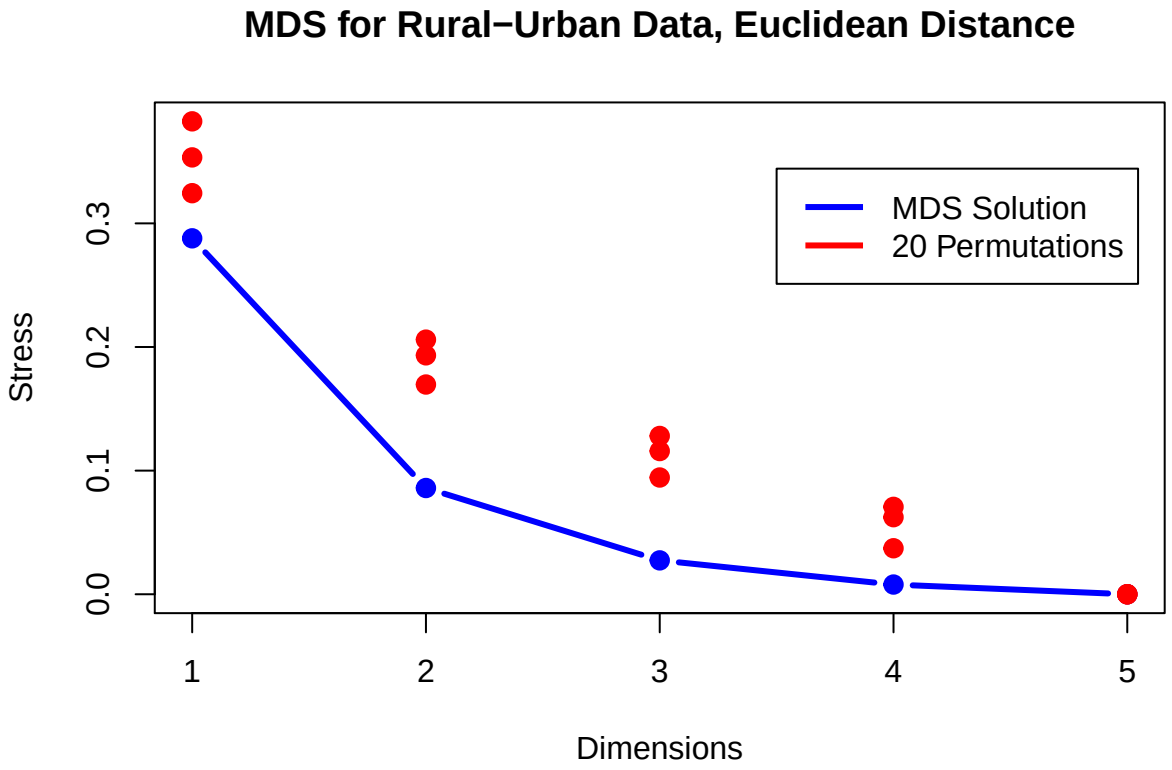
For another visualization of patterns such that the continuous variables shown in blue could be less clustered, we ran detrended correspondence analysis (DCA).



The above detrended correspondence analysis (DCA) plot allows us to better understand the relations between the applied and environmental variables. Higher scores along the first DCA direction are associated with greater proclivity to mask, higher civilian labor force participation, lower poverty, lower unemployment, and lower COVID-19 cases/deaths. This data is sensible and aligns with our previous conclusions about corresponding variables. It is not surprising to observe similar relationships at the state level. Higher scores along the second DCA direction reveal similar relationships: higher COVID-19 cases/deaths, less proclivity to mask, lower unemployment. Interestingly, once again, we see that the second direction indicates higher civilian labor force participation is associated with higher COVID-19 deaths and cases. However, we see that the inverse relationship for these variables is conveyed from the first, and more significant, DCA direction.

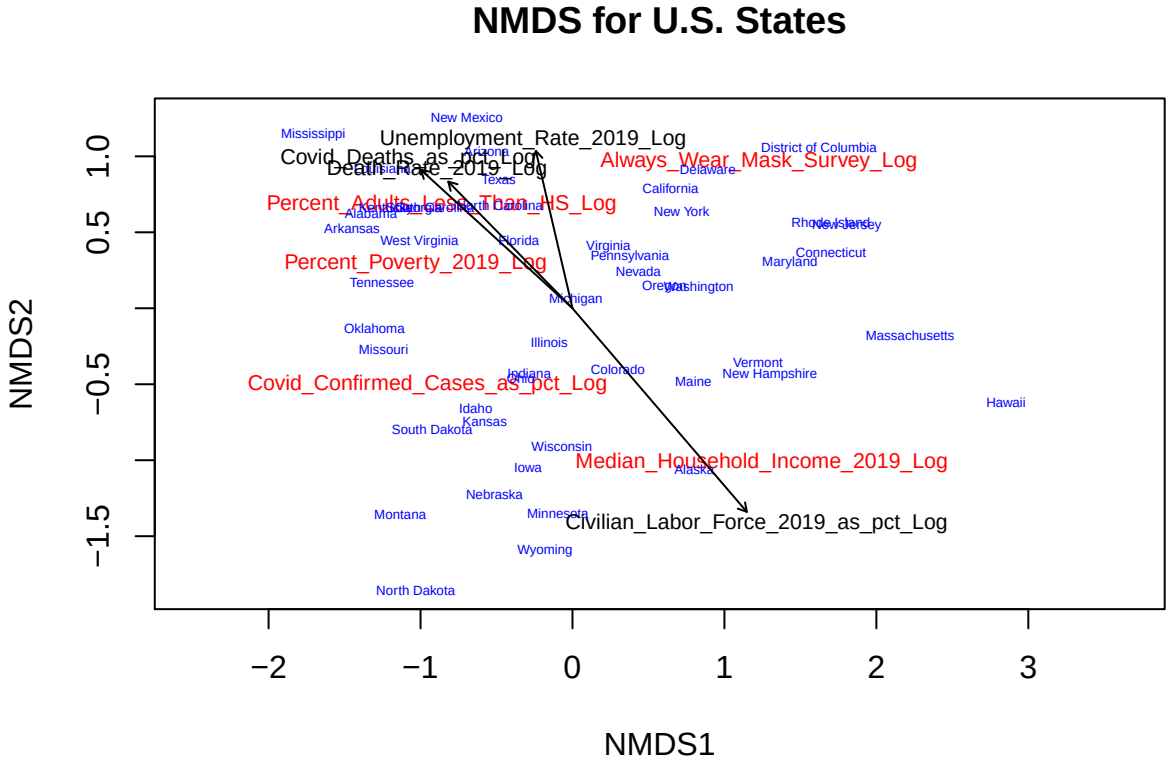
Moreover, we applied multidimensional scaling (MDS).

We made a scree plot of stress of each dimensional solution.



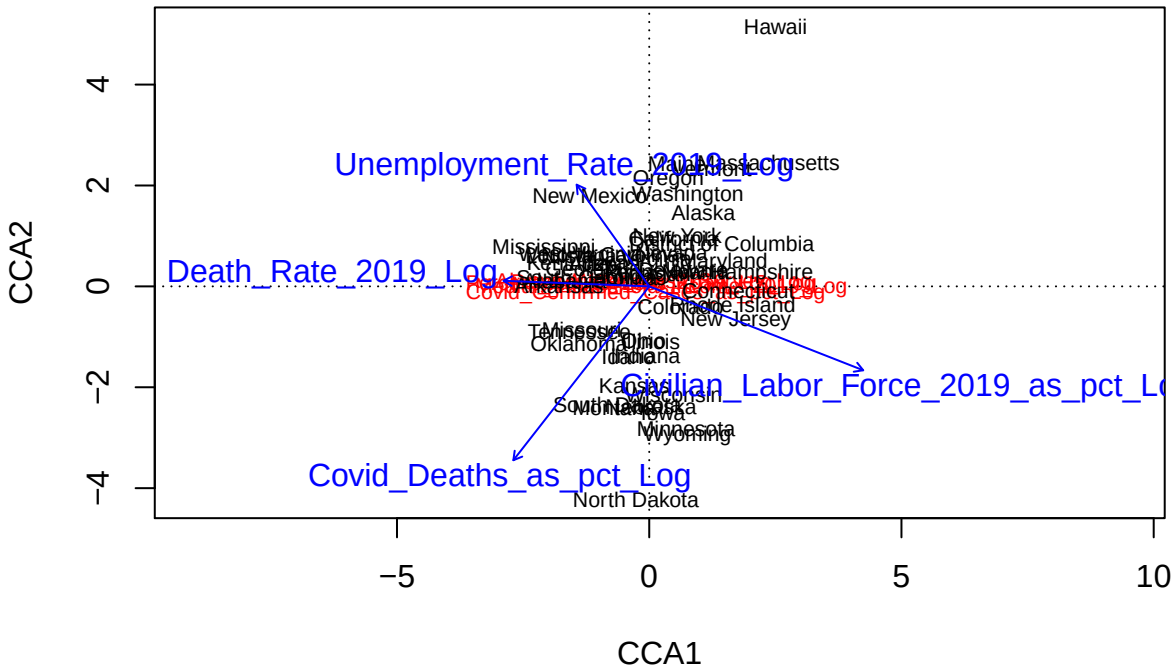
After performing multidimensional scaling for 1-5 dimensions, the above scree plot for stress illustrates an elbow at 2 dimensions. This stress level is below 10% and indicates a good fit. For 3 dimensions, the stress is below 5% and indicates an excellent fit. After 4 dimensions, random chance could result in comparable stress values.

Stress is a measure of the difference between actual pairwise distances and calculated reference distances; a lower stress indicates a better fit. As the dimensions exceeds that of the data (for 5 dimensions), the stress goes to 0.



Our above NMDS plot with overlaid environmental variables indicate similar relationships (particularly along the more significant first direction): states with higher COVID-19 cases/deaths are associated with lower median household income, greater proclivity to mask, greater poverty, greater overall death rate, and greater percent of adults with less than high school education.

We subsequently explored canonical correspondence analysis to, once again, to get a sense of the distribution of U.S. states with respect to both the base and environmental continuous variables.



Although more compact in presentation, canonical correspondence analysis (CCA) similarly demonstrates how states with higher COVID-19 cases/deaths are associated with greater unemployment and greater overall death rate.

Among our ordination results, NMDS seems to provide the most insight. The axes are scaled in such a way that the data clearly illustrates patterns among the states with respect to the base and environmental variables. We see that higher COVID-19 cases/deaths is associated with lower median household income, greater proclivity to mask, greater poverty, greater overall death rate, and greater percent of adults with less than high school education. These trends at the state-level largely reflect what we observed at the county-level.

Conclusions and Discussion

This report examined connections between the economic, education, behavioral, and population data for the 3141 U.S. counties and COVID-19 infection and death rate data.

Using PCA, we reduced the dimensionality of our large dataset to 3 principle components to explain 73% of the total variability. We highlight that there are two main factors that are associated with risk of COVID-19 infection and death: 1) masking behaviors and 2) socioeconomic status. Masking and wealth are associated with lower COVID-19 infection and death rates. Using cluster analysis, we determined which counties are most similar to each other: there are very well-off counties with high mask compliance and low COVID-19 rates, moderately well-off counties with low-mask compliance and high COVID-19 rates, and impoverished counties with high COVID-19 rates. This clustering implies that differences in masking behaviors and COVID-19 infection may not be due to any sort of moral gap but more likely due to a gap in resources - it is a privilege to be able to stay informed on scientific discoveries, purchase masks, work from home, and maintain social distancing. We also note the that impoverished counties have much higher COVID-19 death rates and may have preexisting conditions that worsen its effects and lack quality healthcare or health insurance. Moreover, our ordination techniques for states revealed similar trends: higher COVID-19 infection and death is associated with lower median household income, greater proclivity to mask, greater poverty, greater overall death rate, and greater percent of adults with less than high school education.

We can observe these connections, but we cannot make any cause-and-effect statements based on our current observational study. However, even without knowing the cause, we can say that vaccine and education efforts should be prioritized in underprivileged communities with lower masking rates - these communities are being hit the hardest by COVID-19. Moreover, we see that communities with pre-existing disadvantages prior to the pandemic (e.g., higher unemployment, higher overall death rate, less educated population) are being disproportionately affected by the virus.

Points for Further Analysis

We hope that studies of COVID-19 death and infection rates will continue, even as vaccination rates increase, so we can find the communities who can benefit from public health efforts both now and in the future. We also hope that these public efforts extend beyond just COVID-19 assistance; our work has highlighted the connection between socioeconomic factors and infection and death rates. While we are unable to examine the causal nature of this relationship with this dataset, hopefully future studies will probe at why this connection exists and present solutions.

We note that COVID-19 is a pandemic, impacting the entire world. Though we only studied counties in the United States, it would be worthwhile to study other countries to understand how to prioritize not only vaccination efforts in the U.S. but in the world. Vaccination is a world-wide effort, and none of us are protected until we are all protected.