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Final Project: Clustering Covid Data

Introduction

In the year 2020, both the COVID-19 and president election was happening. Between the Republican candidate (President Trump), Democratic candidate (President Biden), and their followers had differing opinions on wearing masks and the covid vaccine. Those who were generally against wearing masks and the vaccine were supporters of President Trump. During this pandemic plenty of data is collected and can do many interesting analysis on all of this data. For this final project I want to answer the question, "Are counties that are more democratic or more republican more likely to wear a mask and receive the vaccine?" This idea was first presented by Professor Fitzgerald and I wanted to follow up on it.

Method

To answer this question, I decided to use the concepts learned from class on the database (AWS Athena), Julia programming, dimension reduction(PCA), and clustering(Kmeans). Through AWS Athena, I wanted to add on to the existing covid database created created by Facebook surveys with number of votes per candidate, income, and population in a county level. AWS Glue will also be used for its crawling features to make faster queries. To help determine whether counties accept the covid vaccine and wearing masks, two signals from the Facebook survey will be used. The 'smoothed_waccept_covid_vaccine' and 'smoothed_wwearing_mask'. Then PCA will be applied the the numerical data and will be applied to KMeans with 2 clusters.

Data

County level election Result: https://github.com/tonmcg/US_County_Level_Election_Results_08-20/blob/master/2020_US_County_Level_Presidential_Results.csv (https://github.com/tonmcg/US_County_Level_Election_Results_08-20/blob/master/2020_US_County_Level_Presidential_Results.csv)

Income and Population: https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/ (https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/)

In [2]:
```
import Clustering

using MultivariateStats
using Plots
using CSV
using DataFrames
```

SQL Query

In [ ]:
```
SELECT state_name, county_fips, county_name, val_acc_vacc, val_wearing_mask, votes_go
p, votes_dem, total_votes, per_gop,
    per_dem, population, income
FROM
(SELECT state_name, county_fips, county_name, value AS val_acc_vacc, votes_gop, votes
_dem, total_votes, per_gop, per_dem,
    pop_estimate_2019 AS population, median_household_income_2019 AS income
FROM covid, final_data, income_data, pop_data
WHERE covid.geo_type= 'county'
AND signal = 'smoothed_waccept_covid_vaccine'
AND CAST(covid.geo_value AS int) = CAST(final_data.county_fips AS int)
AND CAST(covid.geo_value AS int) = CAST(income_data.fips_txt AS int)
AND CAST(covid.geo_value AS int) = CAST(pop_data.FIPStxt AS int)
AND time_value = 20210101) AS acc_vacc(state_name, county_fips, county_name, val_acc_
vacc, votes_gop, votes_dem,
    total_votes, per_gop, per_dem, population, income)
JOIN
(SELECT geo_value, value AS val_wearing_mask
FROM covid
WHERE geo_type = 'county'
AND signal = 'smoothed_wwearing_mask'
AND time_value = 20210101) AS wear_mask(geo_value, val_wearing_mask)
ON CAST(acc_vacc.county_fips AS int) = CAST(wear_mask.geo_value AS int)
```

Csv file created from the query.

In [3]:
```
df = DataFrame(CSV.File("final_data.csv"))
size(df)
```
Out[3]:
```
(594, 12)
```

In [242]:
```
size(unique(df.state_name))
```
Out[242]:
```
(50,)
```

Biggest percentage of Republican candidate vote by county.

In [249]:
```
df[findmax(df.per_gop)[2],1:6]
```
Out[249]: DataFrameRow (6 columns)

	state_name	county_fips	county_name	val_acc_vacc	val_wearing_mask	votes_gop
	String	Int64	String	Float64	Float64	Int64
382	Louisiana	22063	Livingston Parish	51.3556	73.0268	54877

In [250]:
```
df[findmax(df.per_gop)[2],7:end]
```
Out[250]: DataFrameRow (6 columns)

	votes_dem	total_votes	per_gop	per_dem	population	income
	Int64	Int64	Float64	Float64	Int64	Int64
382	9249	65230	0.841285	0.141791	140789	63852

Biggest percentage of Democratic candidate vote by county.

In [251]:
```
df[findmax(df.per_dem)[2],1:6]
```
Out[251]: DataFrameRow (6 columns)

	state_name	county_fips	county_name	val_acc_vacc	val_wearing_mask
	String	Int64	String	Float64	Float64
228	District of Columbia	11001	District of Columbia	82.9401	97.0779

In [236]:
```
df[findmax(df.per_dem)[2],7:end]
```
Out[236]: DataFrameRow (6 columns)

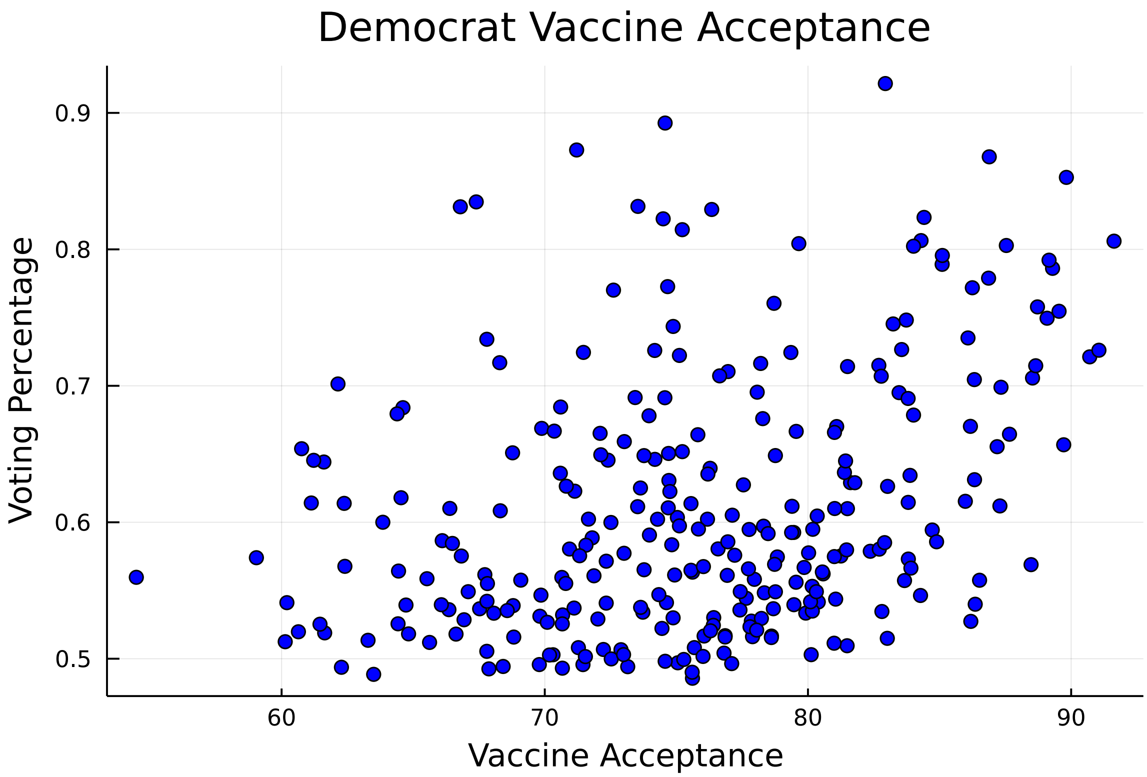
	votes_dem	total_votes	per_gop	per_dem	population	income
	Int64	Int64	Float64	Float64	Int64	Int64
228	317323	344356	0.0539732	0.921497	705749	90395

Creating new dataframe with only numerical data for PCA.

In [17]:

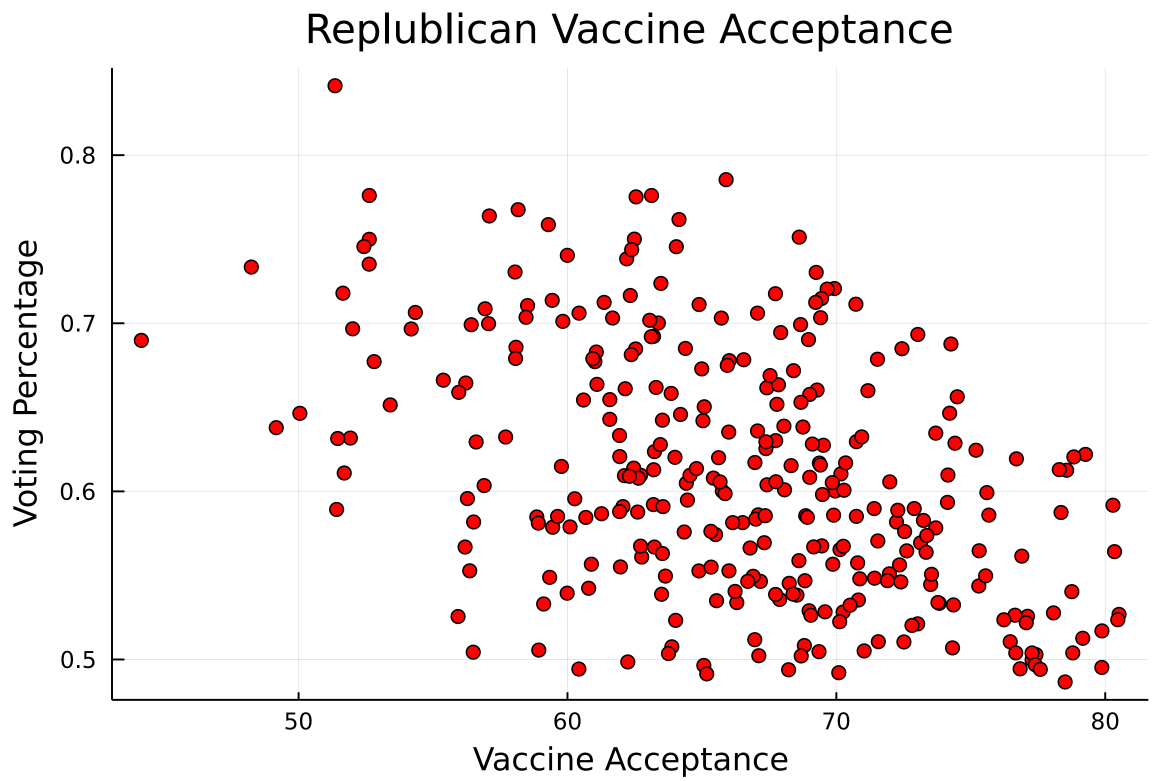
```
dem = df[df.per_dem.>df.per_gop,:]
scatter(dem.val_acc_vacc,dem.per_dem, color = "blue", title= "Democrat Vaccine Acceptance", xlabel= "Vaccine Acceptance", ylabel="Voting Percentage", legend=false)
```

Out[17]:



In [15]:
```
gop = df[df.per_dem.<df.per_gop,:]
scatter(gop.val_acc_vacc,gop.per_gop, color= "red", title= "Replublican Vaccine Accep
tance", xlabel= "Vaccine Acceptance", ylabel="Voting Percentage", legend=false)
```

Out[15]:



Creating new dataframe with only numerical data for PCA.

In [221]:
```
names(df)
```

Out[221]:
```
12-element Vector{String}:
 "state_name"
 "county_fips"
 "county_name"
 "val_acc_vacc"
 "val_wearing_mask"
 "votes_gop"
 "votes_dem"
 "total_votes"
 "per_gop"
 "per_dem"
 "population"
 "income"
```

In [224]:
```
num_df = select(df, Not([:state_name, :county_fips, :county_name]))
names(num_df)
```

Out[224]:
```
9-element Vector{String}:
 "val_acc_vacc"
 "val_wearing_mask"
 "votes_gop"
 "votes_dem"
 "total_votes"
 "per_gop"
 "per_dem"
 "population"
 "income"
```

PCA

In [225]:
```
mtx_df = Matrix(num_df)
tp_mtx = transpose(mtx_df)
pca = fit(PCA, tp_mtx, maxoutdim = 1)
```

Out[225]:
```
PCA(indim = 9, outdim = 1, principalratio = 0.9909325926101895)
```

When the data is projected to 1 dimension it is representative 99% of the variation in the data.

Taking a look at the top loadings in the PCA. These are some of the most populated states, so the counties from these states would be significant.

In [227]:
```
proj = abs.(projection(pca)[:,1])
sorted_proj = sortperm(proj, rev = true)
pca_loadings = df[sorted_proj,:]
```

Out[227]: 9 rows × 12 columns (omitted printing of 6 columns)

	state_name	county_fips	county_name	val_acc_vacc	val_wearing_mask	votes_gop
	String	Int64	String	Float64	Float64	Int64
1	Georgia	13115	Floyd County	68.669	88.2842	28906
2	Colorado	8069	Larimer County	80.5756	95.4249	91489
3	California	6065	Riverside County	74.8758	96.1688	448702
4	California	6041	Marin County	84.4113	96.869	24612
5	Illinois	17143	Peoria County	61.6361	92.3582	38252
6	Arizona	4013	Maricopa County	70.3126	92.1158	995665
7	California	6039	Madera County	68.8322	92.9932	29378
8	Florida	12117	Seminole County	71.2766	90.5598	125241
9	Delaware	10001	Kent County	65.6222	96.5662	41009

KMeans Clustering

In [210]:
```
nclusters = 2

k2 = Clustering.kmeans(tp_mtx, nclusters)
```

Out[210]:
```
Clustering.KmeansResult{Matrix{Float64}, Float64, Int64}([70.65745580017517 75.97
26345304348; 91.19960543555167 95.63957296086956; … ; 335178.00350262696 2.890012
434782609e6; 67226.71278458844 75704.34782608696], [2, 1, 1, 2, 1, 1, 1, 1, 1, 1
…  1, 1, 1, 1, 1, 1, 1, 1, 1, 1], [3.6213596229850273e12, 5.104629508446277e10,
1.1966828408251678e10, 3.147452784448242e11, 5.399537838705872e9, 3.3523341831232
97e10, 3.181732232746765e10, 8.0306904070904e10, 3.482289354649176e10, 5.11710932
7059152e10  …  3.010319277508499e10, 4.533762856591608e10, 2.2217971583720764e10,
1.0731862746749878e9, 5.704179727440933e10, 6.7478046112139755e10, 2.323384914920
6177e10, 1.123837210548294e10, 1.5042704411050415e10, 3.953026323374579e10], [57
1, 23], [571, 23], 1.64975166727693e14, 13, true)
```

In [211]:
```
k2.counts
```

Out[211]:
```
2-element Vector{Int64}:
 571
  23
```

The first cluster has about 96% of the counties and the second cluster has about 4% of the counties.

Looking into the centroids of the 2 clusters.

In [212]:
```
"""
    Find the indices of the data points that are closest to the centroids defined by
 the kmeans clustering.
"""
function close_centroids(knn_model)
    groups = knn_model.assignments
    k = length(unique(groups))
    n = length(groups)
    result = fill(0, k)
    for ki in 1:k
        cost_i = fill(Inf, n)
        group_i = ki .== groups
        cost_i[group_i] = knn_model.costs[group_i]
        result[ki] = argmin(cost_i)
    end
    result
end
cc = close_centroids(k2)
```

Out[212]:
```
2-element Vector{Int64}:
 299
 268
```

Centroid 1

In [254]:
```
df[cc[1],1:6]
```

Out[254]: DataFrameRow (6 columns)

	state_name	county_fips	county_name	val_acc_vacc	val_wearing_mask	votes_gop
	String	Int64	String	Float64	Float64	Int64
299	Oregon	41047	Marion County	63.4975	89.981	79002

In [255]:
```
df[cc[1],7:end]
```

Out[255]: DataFrameRow (6 columns)

	votes_dem	total_votes	per_gop	per_dem	population	income
	Int64	Int64	Float64	Float64	Int64	Int64
299	80872	165534	0.477255	0.488552	347818	64058

Centroid 2

In [252]:
```
df[cc[2],1:6]
```

Out[252]: DataFrameRow (6 columns)

	state_name	county_fips	county_name	val_acc_vacc	val_wearing_mask	votes_gop
	String	Int64	String	Float64	Float64	Int64
268	Florida	12086	Miami-Dade County	73.7255	95.869	532833

In [253]:
```
df[cc[2],7:end]
```

Out[253]: DataFrameRow (6 columns)

	votes_dem	total_votes	per_gop	per_dem	population	income
	Int64	Int64	Float64	Float64	Int64	Int64
268	617864	1156816	0.460603	0.534107	2716940	54991

Splitting the dataframe into their respective clusters.

In [256]:
```
sorted_cls = sortperm(k2.assignments)
c1_idc = sorted_cls[1:k2.counts[1]]
c2_idc = sorted_cls[(k2.counts[1]+1):end]

c1 = df[c1_idc, :]
c2 = df[c2_idc, :]
size(c1)
```

Out[256]:
```
(571, 12)
```

In [257]:
```
size(c2)
```

Out[257]:
```
(23, 12)
```

Examples of counties in cluster 1.

Example 1

In [263]:
```
c1[420, 1:6]
```

Out[263]: DataFrameRow (6 columns)

	state_name	county_fips	county_name	val_acc_vacc	val_wearing_mask	votes_gop
	String	Int64	String	Float64	Float64	Int64
420	New York	36109	Tompkins County	86.0796	97.6017	11096

In [262]:
```
c1[420, 7:end]
```

Out[262]: DataFrameRow (6 columns)

	votes_dem	total_votes	per_gop	per_dem	population	income
	Int64	Int64	Float64	Float64	Int64	Int64
420	33619	45735	0.242615	0.735083	102180	59176

Example 2

In [267]:
```
c1[87, 1:6]
```

Out[267]: DataFrameRow (6 columns)

	state_name	county_fips	county_name	val_acc_vacc	val_wearing_mask	votes_gop
	String	Int64	String	Float64	Float64	Int64
87	Virginia	51700	Newport News city	60.7605	95.7545	26377

In [268]:
```
c1[87, 7:end]
```

Out[268]: DataFrameRow (6 columns)

	votes_dem	total_votes	per_gop	per_dem	population	income
	Int64	Int64	Float64	Float64	Int64	Int64
87	53099	81203	0.324828	0.653904	179225	53022

Examples of counties in cluster 2.

Example 1

In [270]:
```
c1[17, 1:6]
```

Out[270]: DataFrameRow (6 columns)

	state_name	county_fips	county_name	val_acc_vacc	val_wearing_mask	votes_gop
	String	Int64	String	Float64	Float64	Int64
17	New Jersey	34035	Somerset County	80.1823	94.8784	71996

In [271]:
```
c1[17, 7:end]
```

Out[271]: DataFrameRow (6 columns)

	votes_dem	total_votes	per_gop	per_dem	population	income
	Int64	Int64	Float64	Float64	Int64	Int64
17	111173	186891	0.38523	0.594855	328934	112722

Example 2

In [272]:
```
c1[3, 1:6]
```

Out[272]: DataFrameRow (6 columns)

	state_name	county_fips	county_name	val_acc_vacc	val_wearing_mask	votes_gop
	String	Int64	String	Float64	Float64	Int64
3	Colorado	8069	Larimer County	80.5756	95.4249	91489

In [273]:
```
c1[3, 7:end]
```

Out[273]: DataFrameRow (6 columns)

	votes_dem	total_votes	per_gop	per_dem	population	income
	Int64	Int64	Float64	Float64	Int64	Int64
3	126120	224338	0.407818	0.562187	356899	75332

Conclusion

I originally hypothesized counties with higher democratic votes would have higher acceptance of the vaccine and are more willing to wear masks. By the looks of the centroids and examples, the clustering could support this hypothesis. In general, most counties who voted for the democratic candidate had high acceptance of the vaccine and were willing to wear masks. Although, some counties had less acceptance of the vaccine also voted for the democratic candidate and 96% of the counties were in one cluster. There are a few reasons that I could think of that would cause this. One could be the estimates and erros from the Facebook surveys. The surveys tried to estimate the us population through their users and there could be errors on the representation of the population. Another is the amount of data to cluster because there are only 594 counties with data on the date pf 1/1/2021. If I were to expand on the data size, I would look into applying time series into the clustering to increase the pool. Also with this clustering, I would do more statiscal analysis to see relations within the data to draw a better conclusion. Applying some feature selection to determine which feature have the better deciding factors. Adding features such as unemployment or education would be also interesting to look at. Regardless, there is so much data from covid that are interesting to analyze and would like keep exploring it more.