Baystate Banner: LatinX Republican Support (Spring 2021)		
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Organization	Baystate Banner	
Organization Description	The Bay State Banner is an African American owned news weekly that reports on the political, economic, social, and cultural issues that are of interest to African American and English speaking Latinos in Boston and throughout New England.	
Project Type	Data Science	
Project Description	The client would like to understand the components of support for Republicans over the time period of 2015-2020 including Presidential elections and the Governor's races. The goal of the project is to find whether or not there is a significant difference in the voting pattern of the LatinX community from 2016 to 2020. We will be collecting data from cities with a majority LatinX population and non-LatinX populations. We will then compare the two populations to see whether there is a significant difference in voting patterns between the LatinX community and the control group(which has voted Republican consistently in the past). If there is a significant difference between the communities, we will analyze the various changes from 2016 to 2020 in those communities. The main goal is to conclude which LatinX voters changed their votes and which voters stayed consistent.	
Data Sets	 PD43 MA state portal 2016 and 2020 Presidential races 2014 and 2018 MA Governor (General Elections) Census data (Demographics) 6 cities Census data 2019 Lawrence: 2016 and 2019 Lynn: 2016 and 2019 Springfield: 2016 and 2019 	

Southwick: 2016 and 2019
 Acushnet: 2016 and 2019
 Douglas: 2016 and 2019
 Optional Support data

LatinX Origin Demographics (2014)

Suggested Steps

Step one: Collect city voter & demographic data of majority LatinX towns (~80%)

- Lawrence
- Lynn
- Springfield

and compare with representative mostly white towns very likely to vote Republican as control groups

- Southwick
- Acushnet
- Douglas

About the data:

- Voter data includes total ballots cast, registered voters, eligible voters, and demographics for that city.
- Election races will include 2016 and 2020 Presidential races as well as 2014 and 2018 MA Governor-general elections.

Step two: Use pandas to read through csv files and convert to data frames. Only keep key attributes for demographic data (zip code, estimated total pop, LatinX sub-group pop, and voting age pop (18+)) and election data (city zip codes, city names, total votes per candidate, total votes)

Step three: Relate city election data to city demographic data (either via each city's zip codes or precincts). Analyze different kinds of LatinX voters supporting Trump - Mexican, Dominican, Cuban American. Where is their support concentrated? How did their support change from 2016 to 2020

Step three: Examine the difference between LatinX people registered as Democrat, Republican, Independent in these different geographic and elections.

Step four: Complete analysis on correlations between how these towns to vote, do they move with each other in different elections>

Step five: Complete data visualizations based to present which neighborhoods, cities, and districts have higher levels of support for Donald Trump.

Strategic questions	 How has support for Trump shifted across LatinX sub-groups from 2016 to 2020? Was there a significant shift? What is the breakdown of LatinX sub-groups in their support for Democratic vs. Republican candidates? Which LatinX groups exhibited changed their votes and which groups remained the same?
Additional Information	Tools & Methods
	<u>Data pre-processing:</u> Pandas to convert csv files into data frames, NumPy for processing and organizing the pre-processed data
	<u>Data Visualization:</u> Matplotlib, Seaborn, Tableau for all kinds of interactive visualizations
	Weekly Meeting Schedule: Wednesdays 11am - 12:30pm EST

Potential Risks and Limitations:

- Lack of connection between city election results and city demographic data, i.e. unable
 to break down city election results by demographics as we are only given each city's
 aggregate election results
- 2. Difficult to apply clustering methods as we are only given aggregate data for demographics and election results for each city (lack of large dataset)
- 3. The conclusion on voting pattern changes may not be concrete due to the other factors such as changes in voter turnout or each demographic's population which is not indicative of a change in preference for a political candidate.

General Questions:

- 1. How can we combine the election data with the demographic data?
 - a. It will be difficult to combine data frames because we cannot correspond the zip codes from the demographic data to the precincts in the election data
 - b. Can't correlate changes in demographics to changes in election results
 - c. Worst case scenario, should we combine data frames based on the city?
- 2. Should we organize election data based on Republicans vs Non Republicans rather than Republicans vs Democrats vs Independents?
- 3. We can't directly answer any of the key questions until we are able to relate election data to demographic data

Key Question Answers:

1. In our non-control group cities (Springfield, Lawrence, Lynn), Springfield saw a 1.79 percentage point increase in LatinX population (relative to the city's total population) and a 5.13 percentage point increase in Trump votes(across all races). For Lawrence, there was a 3.44 percentage point increase in LatinX population(relative to the city's total population) and a 10.85 percentage point increase in Trump votes(across all races). For Lynn, there was a 4.79 percentage point increase in LatinX population(relative to the city's total population) and 2.96 percentage point increase in Trump votes(across all races).

Listed below are the screenshots of the code for the preprocessed data:

```
In [1]: import pandas as pd
              import numpy as np
  In [2]: acs2016 = pd.read_csv('2016data.csv')
acs2019 = pd.read_csv('2019data.csv')
  In [3]: acs2016
  Out [3]:
                                                                                      Percent
Margin of
Error!!SEX
                                                          Margin of
Error!!SEX
AND
AGE!!Total
                                                                                                                     Margin of
Error!!SEX AND
AGE!!Total
                                                                                                                                                             Percent Margin
of Error!!SEX
AND AGE!!Total
                                                                                                    Estimate!!SEX
AND AGE!!Total
population!!Male
                                                                                                                                          Percent!!SEX
AND AGE!!Total
population!!Male
                                                                         AND
AGE!!Total
                                                                                                                                                                                   POPULA
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                                    ZCTA5
01077
                                                                                                                                                      48.2
                                                   9650
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                                                   2430
                                                                 312
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01105
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                       1105
                                                  11576
                                                                 814
                                                                              11576
                                                                                              (X)
                                                                                                               5585
                                                                                                                                    458
                                                                                                                                                      48.2
                                                                 753
                                                                                                                                                                          2.1 ...
                                    ZCTA5
  In [4]: acs2019
  In [5]: acs2016['Zipcode'] = acs2016['Zipcode'].astype(str)
acs2019 = acs2019.rename(columns={"id":"Zipcode"})
   In [6]: acs2019['Zipcode'] = acs2019['Zipcode'].astype(str)
  In [7]: acs2016['Zipcode'] = acs2016['Zipcode'].str.zfill(5)
acs2019['Zipcode'] = acs2019['Zipcode'].str.zfill(5)
   In [9]: # Estimate!!HISPANIC OR LATINO AND RACE!!Total population!!Hispanic or Latino (of any race)!!Mexican
# Estimate!!HISPANIC OR LATINO AND RACE!!Total population!!Hispanic or Latino (of any race)!!Puerto Rican
# Estimate!!HISPANIC OR LATINO AND RACE!!Total population!!Hispanic or Latino (of any race)!!Cuban
# Estimate!!HISPANIC OR LATINO AND RACE!!Total population!!Hispanic or Latino (of any race)!!Other Hispanic or Latin
# Estimate!!HISPANIC OR LATINO AND RACE!!Total population!!Not Hispanic or Latino
# Estimate!!CITIZEN, VOTING AGE POPULATION!!Citizen, 18 and over population
# Estimate!!CITIZEN, VOTING AGE POPULATION!!Citizen, 18 and over population
                # Estimate Total population
                processed2016 = acs2016[['Zipcode','Estimate Total population','Estimate!!HISPANIC OR LATINO AND RACE!!Total populat
  In [10]: processed2019 = acs2019[['Zipcode', 'Estimate Total population', 'Estimate!!HISPANIC OR LATINO AND RACE!!Total populat
  In [11]: processed2016 = processed2016.rename(columns={'Estimate!!HISPANIC OR LATINO AND RACE!!Total population!!Hispanic or
  In [12]: processed2019 = processed2019.rename(columns={'Estimate!!HISPANIC OR LATINO AND RACE!!Total population!!Hispanic or
city.append('Douglas')
else:
    city.append('Missing City Name, Fix')
     In [15]: processed2016.insert(1,"City",city)
      In [16]: processed2016
 In [20]: pres2016 = pd.read_csv('2016PresidentPrecinct.csv')
    pres2020 = pd.read_csv('2020PresidentPrecint.csv')
    gov2018 = pd.read_csv('2018gov.csv')
  In [21]: pres2020.head()
  Out[21]:
                    City/Town Ward Pct Joseph R. Biden, Jr. Donald J. Trump Jo Jorgensen Howard Hawkins All Others No Preference Blanks Total Votes Cast
                 0 NaN NaN NaN Democratic
                                                                          Republican Libertarian Green-Rainbow
                                                                                                                                 NaN
                                                                                                                                                  NaN
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                 4 Abington - 4
                                                             1,117
                                                                                 904
                                                                                                   28
                                                                                                                                                   0.0
                                                                                                                                                                            2,088
  In [22]: gov2018.head()
  Out[22]:
                    City/Town Ward Pct Baker and Polito Gonzalez and Palfrey All Others Blanks Total Votes Cast
                 0
                       NaN NaN NaN Republican
                                                                           Democratic
                                                                                              NaN
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                                                                                                                          NaN
                                                                                   311
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                      Abington
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                 3 Abington
                                                          1,047
                                                                                   325
                                                                                                                          1,446
                 4 Abington - 4 1,247
                                                                    350
                                                                                         1 68
                                                                                                                  1,666
 In [25]: procpres2016 = pres2016[['City/Town','Pct','Clinton/ Kaine','Trump/ Pence','Total Votes Cast']]
    procpres2020 = pres2020[['City/Town','Pct','Joseph R. Biden, Jr.','Donald J. Trump','Total Votes Cast']]
    procgov2018 = gov2018[['City/Town','Pct','Gonzalez and Palfrey','Baker and Polito','Total Votes Cast']]
```

```
In [26]: procpres2016.drop([0])
                            procpres2020.drop([0])
                           procqov2018.drop([0])
  Out[26]:
                                          City/Town Pct Gonzalez and Palfrey Baker and Polito Total Votes Cast
                                   1
                                            Abington
                                                                                                           311
                                                                                                                                             984
                                                                                                                                                                             1,343
                                   2
                                         Abington
                                                                                                                                              967
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                                                                    3
                                                                                                           325
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                                                                                                                                                                            1,446
                                   3
                                             Abington
                                                                                                            350
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                                            Yarmouth
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                                          Yarmouth
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                              2174 TOTALS NaN
                                                                                                    885,770
                                                                                                                                   1,781,341
                                                                                                                                                          2,752,665
  In [28]: pres2016 = procpres2016[(procpres2016['City/Town'] == 'Lawrence') | (procpres2016['City/Town'] == 'Springfield') | (procpres2016['City/Town'] == 'Spring
In [30]: pres2020 = procpres2020[(procpres2020['City/Town'] == 'Lawrence') | (procpres2020['City/Town'] == 'Springfield')| (procpres2020['City/Town'] == 'Springfield')|
In [31]: gov2018 = procgov2018[(procpres2016['City/Town'] == 'Lawrence') | (procgov2018['City/Town'] == 'Springfield')| (proc
                          <ipython-input-31-ef57abbf539a>:1: UserWarning: Boolean Series key will be reindexed to match DataFrame index.
                          gov2018 = procgov2018[(procpres2016['City/Town'] == 'Lawrence') | (procgov2018['City/Town'] == 'Springfield')| (procgov2018['City/Town'] == 'Lynn')|(procgov2018['City/Town'] == 'Acushnet')|(procgov2018['City/Town'] == 'Southwick')|(procgov2018['City/Town'] == 'Douglas')]
In [33]: pres2016 = pres2016.reset_index()
pres2016 = pres2016.drop(columns=['index'])
                         pres2020 = pres2020.reset_index()
                          pres2020 = pres2020.drop(columns=['index'])
                          gov2018 = gov2018.reset_index()
                          gov2018 = gov2018.drop(columns=['index'])
     In [37]: processed2016.to_csv(index = False)
                              processed2019.to_csv(index = False)
                              pres2016.to_csv(index = False)
pres2020.to_csv(index = False)
                              gov2018.to_csv(index = False)
                              #to_excel(r'Demo2016.xlsx', index = False)
#processed2019.to_excel(r'Demo2019.xlsx', index = False)
                              #pres2016.to_excel(r'Pres2016.xlsx', index = False)
#pres2020.to_excel(r'Pres2020.xlsx', index = False)
#gov2018.to_excel(r'Gov2018.xlsx', index = False)
```