IS843 Analyzing the Impact of Education on Voter Turnout in MA & NY Counties

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May 1, 2022

0.1 Contents

1 Abstract

After exploring and analyzing all of our data, we believe that higher levels of education lead to higher turnout, and that such an effect is particularly pronounced in primary elections. Interestingly, primary election turnout is positively correlated with voters with higher than high school education and negatively correlated with voters with high school or less. For the general election, those with a bachelor's degree or higher are more likely to vote while some college students or those with lower levels of education are less likely to vote. This is intuitive because people with higher levels of education tend to be more civic-minded, exercise their right to vote, and are more interested in participating in political activities. After analyzing the effect of education level on turnout, we also tried to find if there were other factors that were strongly correlated with education level and had an effect on turnout. One of the factors we examined was income level, as we believe that higher levels of education would lead to higher levels of income. But the effect of income level on turnout is not very clear and is somewhat mixed: for general elections, any income level has a negative effect while for primary elections any income level has a positive effect. If we had the opportunity and resources to conduct a deeper study, we would be interested in conducting a study at the individual voter level, including how each voter voted: whether they voted in person or by mail, or whether different levels of education and income would lead to different levels of free time and thus affect willingness to vote.

2 Introduction

Voter participation is critical as it cements the legitimacy of any democratic system. Democratic governments rely on high voter turnout to maintain a democratic structure. With the overall racial and ethnic diversity of the United States increasing dramatically over the last few decades, according to U.S. Census Bureau data, it is crucial to consider the effect of diversity on voter turnout. It is well-known that voting disparity exists among different races and communities, but there is no clear answer. Further data analysis on the subject is required in order to answer that question.

3 Problem Statement

This project aims at shedding some light on the issue of disparity between voter turnout and education level. **Our team hopes to determine if there is any disparity in the voter turnout between households who have completed varying degrees of education.** We will begin our analysis by looking at the east coast region because, through our initial search, we found a more significant disparity in education levels in the east coast region. This will lead to an interesting analysis. We will compare the data points at the county level to account for variations in education level and voter turnout across different parts of each state. We believe that this analysis can be further expanded to consider the types of employment, e.g., do white-collar jobs have an association or impact on voter turnout as well? Therefore, we will also consider those factors. We will be using the Educational Attainment data from the US Census American Community Survey to aid our analysis.

4 Data Description

4.1 Voter data

In the past, the global economy was not as data-driven today. Data seems to be available and easy to access via the Internet from companies to governments. But this data availability was not always the case. While data analysis is only a few decades old, the quantity of data has grown exponentially. Therefore, big data techniques are as relevant as ever to handle the vast volumes of data.

One of the datasets that we analyzed pertains to voter data. Using Boston University's subscription to national voter files, we could attain voter data for every state in the U.S. The voter files contain records for every registered voter in the U.S. The description of the voter data is as follows:

```
- A voter file exists for each state
- Each file contains geographic, demographic, and household information
- Each file contains the history of voting for each registered voter
```

While the voter files contain several columns, we anticipate that only a subset of columns will be relevant to our analysis. A few of these columns are related to the education characteristics of voters as well as income and demographic data.

4.2 Education data

The second dataset that we will be using is regarding education. This dataset was obtained from the US Census Bureau, and it contains columns describing the name of the voter, educational background, race characteristics, and other demographic qualities. The data is at the voter level for the population of 18 to 24-year-olds individuals living in the United States in 2020. While the data is at the voter level, we decided to analyze both datasets based on the county level to have more consistency, breadth, and depth of data points between both datasets.

5 Data Ingestion and Cleansing

5.1 Imports

[1]:
```
##Import required functions
from collections import defaultdict
from pyspark.ml.feature import RFormula, StandardScaler
from pyspark.ml.regression import LinearRegression, DecisionTreeRegressor,␣
 ↪RandomForestRegressor
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.tuning import ParamGridBuilder, TrainValidationSplit
from pyspark.sql.functions import regexp_extract, regexp_replace, col, upper
from pyspark.sql.types import DoubleType
from pyspark.sql.functions import substring
from pyspark.sql.types import IntegerType

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

5.2 Read Datasets from Bucket

[3]:
```
# We used the following code to read the data, check our schema to see if data␣
 ↪is loaded properly
data = "gs://project_bucket_real/notebooks/jupyter/data/"
df_ma = spark.read.format("csv")\
    .option("inferSchema", "True")\
    .option("header", "True")\
    .option("nullValue", "NA")\
    .option("delimiter", "	")\
    .load(data + 'VM2Uniform--MA--2021-01-19.tab')
df_ma = df_ma.select(
                    'County','Voters_FIPS',
                    'Board_of_Education_District',␣
 ↪'Board_of_Education_SubDistrict',
                    'County_Board_of_Education_District',␣
 ↪'County_Board_of_Education_SubDistrict',
                    'Education_Commission_District',␣
 ↪'Educational_Service_District',
                    'Educational_Service_Subdistrict',␣
 ↪'Regional_Office_of_Education_District',
                    'CommercialData_Education',␣
 ↪'CommercialData_AreaMedianEducationYears',
```

```
                    ␣
↪'CommercialDataLL_Interest_in_Education_Online_In_Household',
                    'ElectionReturns_G08CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G10CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G12CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G14CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G16CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G18CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_P08CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_P10CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_P12CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_P14CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_P16CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_P18CountyTurnoutAllRegisteredVoters',
                    'CommercialData_StateIncomeDecile',
                    'CommercialData_EstimatedHHIncome'
                    )
df_ma.printSchema()
```

```
root
 |-- County: string (nullable = true)
 |-- Voters_FIPS: integer (nullable = true)
 |-- Board_of_Education_District: string (nullable = true)
 |-- Board_of_Education_SubDistrict: string (nullable = true)
 |-- County_Board_of_Education_District: string (nullable = true)
 |-- County_Board_of_Education_SubDistrict: string (nullable = true)
 |-- Education_Commission_District: string (nullable = true)
 |-- Educational_Service_District: string (nullable = true)
 |-- Educational_Service_Subdistrict: string (nullable = true)
 |-- Regional_Office_of_Education_District: string (nullable = true)
 |-- CommercialData_Education: string (nullable = true)
 |-- CommercialData_AreaMedianEducationYears: integer (nullable = true)
 |-- CommercialDataLL_Interest_in_Education_Online_In_Household: string
(nullable = true)
 |-- ElectionReturns_G08CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G10CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G12CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G14CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G16CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G18CountyTurnoutAllRegisteredVoters: string (nullable =
true)
```

```
 |-- ElectionReturns_P08CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P10CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P12CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P14CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P16CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P18CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- CommercialData_StateIncomeDecile: integer (nullable = true)
 |-- CommercialData_EstimatedHHIncome: string (nullable = true)
```

[4]:
```
# Read NY dataset
df_ny = spark.read.format("csv")\
    .option("inferSchema", "True")\
    .option("header", "True")\
    .option("nullValue", "NA")\
    .option("delimiter", "	")\
    .load(data + 'VM2Uniform--NY--2021-03-15.tab')
```

[5]:
```
# Take a subset of columns related to education as well as voter turnout data
df_ny = df_ny.select(
                    'County', 'Voters_FIPS',
                    'Board_of_Education_District',␣
 ↪'Board_of_Education_SubDistrict',
                    'County_Board_of_Education_District',␣
 ↪'County_Board_of_Education_SubDistrict',
                    'Education_Commission_District',␣
 ↪'Educational_Service_District',
                    'Educational_Service_Subdistrict',␣
 ↪'Regional_Office_of_Education_District',
                    'CommercialData_Education',␣
 ↪'CommercialData_AreaMedianEducationYears',
                   ␣
 ↪'CommercialDataLL_Interest_in_Education_Online_In_Household',
                    'ElectionReturns_G08CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G10CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G12CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G14CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G16CountyTurnoutAllRegisteredVoters',
                    'ElectionReturns_G18CountyTurnoutAllRegisteredVoters',
```

```python
                         'ElectionReturns_P08CountyTurnoutAllRegisteredVoters',
                         'ElectionReturns_P10CountyTurnoutAllRegisteredVoters',
                         'ElectionReturns_P12CountyTurnoutAllRegisteredVoters',
                         'ElectionReturns_P14CountyTurnoutAllRegisteredVoters',
                         'ElectionReturns_P16CountyTurnoutAllRegisteredVoters',
                         'ElectionReturns_P18CountyTurnoutAllRegisteredVoters',
                         'CommercialData_StateIncomeDecile',
                         'CommercialData_EstimatedHHIncome'
                         )
# Check our NY sub dataset schema
df_ny.printSchema()
```

```
root
 |-- County: string (nullable = true)
 |-- Voters_FIPS: integer (nullable = true)
 |-- Board_of_Education_District: string (nullable = true)
 |-- Board_of_Education_SubDistrict: string (nullable = true)
 |-- County_Board_of_Education_District: string (nullable = true)
 |-- County_Board_of_Education_SubDistrict: string (nullable = true)
 |-- Education_Commission_District: string (nullable = true)
 |-- Educational_Service_District: string (nullable = true)
 |-- Educational_Service_Subdistrict: string (nullable = true)
 |-- Regional_Office_of_Education_District: string (nullable = true)
 |-- CommercialData_Education: string (nullable = true)
 |-- CommercialData_AreaMedianEducationYears: integer (nullable = true)
 |-- CommercialDataLL_Interest_in_Education_Online_In_Household: string
(nullable = true)
 |-- ElectionReturns_G08CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G10CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G12CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G14CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G16CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G18CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P08CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P10CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P12CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P14CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P16CountyTurnoutAllRegisteredVoters: string (nullable =
```

```
true)
 |-- ElectionReturns_P18CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- CommercialData_StateIncomeDecile: integer (nullable = true)
 |-- CommercialData_EstimatedHHIncome: string (nullable = true)
```

[6]:
```
# Read the supplemental education dataset from US Census Bureau
df_edu = spark.read.format("csv")\
    .option("inferSchema", "True")\
    .option("header", "True")\
    .option("nullValue", "(X)")\
    .load(data + 'MA&NY_ASCCT5Y2020.csv')
```

The Education dataset from US Census Bureau contains datatype inconsistency issue, which is caused by null values with more than one respresentations.

5.2.1 Concactenate MA and NY datasets together

[7]:
```
df_east = df_ma.union(df_ny)
```

[8]:
```
df_east.count()
```

[8]:
```
17143289
```

5.3 Data Cleaning

First, we'll look at a small sample of our dataset (small enough to fit in-memory for conversion and use in Pandas) and extrapolate findings on the sampled dataset for which columns to ultimately retain for full analysis on the full dataset.

Later on, we'll also use this smaller data set for early parts of exploratory data analysis, in which we'll show why the MA and NY data set alone is flawed for comparing education and voter turnout. This will motivate our use of the US Census data set on educational attainment. We will use the full US Census educational attainment data set, which presents data at the county-level. Therefore, we can also continue using our subset of the voter turnout data set, since county-level turnout is available in each row and using the full data set only adds more voter-level information. The amount of county-level information available is the same regardless of whether we use the sampled voter turnout data or the full voter turnout data, so we will continue to use the former for efficiency.

5.4 Keep columns of interest

[9]:
```
# Sample our MA + NY voter turnout dataset first
df_east_sample = df_east.sample(withReplacement = False, fraction = 0.25, seed␣
↪= 42)

# Convert to Pandas
```

```
pd_east_sample = df_east_sample.toPandas()

pd_east_sample.head()
```

```
22/05/01 23:56:40 WARN org.apache.spark.sql.catalyst.util.package: Truncated the
string representation of a plan since it was too large. This behavior can be
adjusted by setting 'spark.sql.debug.maxToStringFields'.
```

[9]:

```
       County  Voters_FIPS Board_of_Education_District  \
0  BARNSTABLE            1                        None
1  BARNSTABLE            1                        None
2  BARNSTABLE            1                        None
3  BARNSTABLE            1                        None
4  BARNSTABLE            1                        None

  Board_of_Education_SubDistrict County_Board_of_Education_District  \
0                           None                               None
1                           None                               None
2                           None                               None
3                           None                               None
4                           None                               None

  County_Board_of_Education_SubDistrict Education_Commission_District  \
0                                  None                          None
1                                  None                          None
2                                  None                          None
3                                  None                          None
4                                  None                          None

  Educational_Service_District Educational_Service_Subdistrict  \
0                         None                            None
1                         None                            None
2                         None                            None
3                         None                            None
4                         None                            None

  Regional_Office_of_Education_District  …  \
0                                  None  …
1                                  None  …
2                                  None  …
3                                  None  …
4                                  None  …

  ElectionReturns_G16CountyTurnoutAllRegisteredVoters  \
0                                                79%
1                                                79%
2                                                79%
```

```
3                                                79%
4                                                79%

   ElectionReturns_G18CountyTurnoutAllRegisteredVoters  \
0                                                68%
1                                                68%
2                                                68%
3                                                68%
4                                                68%

  ElectionReturns_P08CountyTurnoutAllRegisteredVoters  \
0                                                18%
1                                                18%
2                                                18%
3                                                18%
4                                                18%

  ElectionReturns_P10CountyTurnoutAllRegisteredVoters  \
0                                                26%
1                                                26%
2                                                26%
3                                                26%
4                                                26%

  ElectionReturns_P12CountyTurnoutAllRegisteredVoters  \
0                                                18%
1                                                18%
2                                                18%
3                                                18%
4                                                18%

  ElectionReturns_P14CountyTurnoutAllRegisteredVoters  \
0                                                22%
1                                                22%
2                                                22%
3                                                22%
4                                                22%

  ElectionReturns_P16CountyTurnoutAllRegisteredVoters  \
0                                                19%
1                                                19%
2                                                19%
3                                                19%
4                                                19%

  ElectionReturns_P18CountyTurnoutAllRegisteredVoters  \
0                                                27%
```

```
1                                                    27%
2                                                    27%
3                                                    27%
4                                                    27%

  CommercialData_StateIncomeDecile CommercialData_EstimatedHHIncome
0                              2.0                    $50000-74999
1                              3.0                    $75000-99999
2                              6.0                  $125000-149999
3                              5.0                  $125000-149999
4                              3.0                  $200000-249999

[5 rows x 27 columns]
```

[10]:
```python
# Caching the sample
df_east_sample = df_east_sample.repartition(20)
print("data was re-partitioned to {} partitions!".format(df_east_sample.rdd.
 ↪getNumPartitions()))

# Setting the number of shuffle partitions
spark.conf.set("spark.sql.shuffle.partitions", "20")

# Caching the DataFrame
df_east_sample.cache()
```

```
[Stage 10:=====================================================>(281 + 1) / 282]

data was re-partitioned to 20 partitions!
```

[10]:
```
DataFrame[County: string, Voters_FIPS: int, Board_of_Education_District: string,
Board_of_Education_SubDistrict: string, County_Board_of_Education_District:
string, County_Board_of_Education_SubDistrict: string,
Education_Commission_District: string, Educational_Service_District: string,
Educational_Service_Subdistrict: string, Regional_Office_of_Education_District:
string, CommercialData_Education: string,
CommercialData_AreaMedianEducationYears: int,
CommercialDataLL_Interest_in_Education_Online_In_Household: string,
ElectionReturns_G08CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_G10CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_G12CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_G14CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_G16CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_G18CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_P08CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_P10CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_P12CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_P14CountyTurnoutAllRegisteredVoters: string,
ElectionReturns_P16CountyTurnoutAllRegisteredVoters: string,
```

```
ElectionReturns_P18CountyTurnoutAllRegisteredVoters: string,
CommercialData_StateIncomeDecile: int, CommercialData_EstimatedHHIncome: string]
```

[11]:
```
# Take a look at percentage data missing of our selected columns
pd_east_sample.isnull().sum()/len(pd_east_sample)
```

[11]:
```
County                                                 0.000000
Voters_FIPS                                            0.000000
Board_of_Education_District                            1.000000
Board_of_Education_SubDistrict                         1.000000
County_Board_of_Education_District                     1.000000
County_Board_of_Education_SubDistrict                  1.000000
Education_Commission_District                          1.000000
Educational_Service_District                           1.000000
Educational_Service_Subdistrict                        1.000000
Regional_Office_of_Education_District                  1.000000
CommercialData_Education                               0.403178
CommercialData_AreaMedianEducationYears                0.038577
CommercialDataLL_Interest_in_Education_Online_In_Household     0.949330
ElectionReturns_G08CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_G10CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_G12CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_G14CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_G16CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_G18CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P08CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P10CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P12CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P14CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P16CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P18CountyTurnoutAllRegisteredVoters    0.000000
CommercialData_StateIncomeDecile                       0.038577
CommercialData_EstimatedHHIncome                       0.023909
dtype: float64
```

[12]:
```
# Drop columns with over 50% of missing values
pd_east_sample.drop(columns = ['Board_of_Education_District',␣
 ↪'Board_of_Education_SubDistrict',
                               'County_Board_of_Education_District',␣
 ↪'County_Board_of_Education_SubDistrict',
                               'Education_Commission_District',␣
 ↪'Educational_Service_District',
                               'Educational_Service_Subdistrict',␣
 ↪'Regional_Office_of_Education_District',
                              ␣
 ↪'CommercialDataLL_Interest_in_Education_Online_In_Household'], inplace =␣
 ↪True)
```

[13]:
```python
# Examine income columns
pd_east_sample.CommercialData_StateIncomeDecile.value_counts()
```

[13]:
```
9.0    469684
8.0    455561
7.0    436350
6.0    424984
5.0    415066
4.0    397687
3.0    396298
0.0    379305
1.0    373237
2.0    373181
Name: CommercialData_StateIncomeDecile, dtype: int64
```

[14]:
```python
pd_east_sample.CommercialData_EstimatedHHIncome.unique()
```

[14]:
```
array(['$50000-74999', '$75000-99999', '$125000-149999', '$200000-249999',
       '$150000-174999', None, '$250000+', '$100000-124999',
       '$35000-49999', '$175000-199999', '$15000-24999', '$1000-14999',
       '$25000-34999'], dtype=object)
```

[15]:
```python
df_east_sample = df_east_sample.drop('Board_of_Education_District',␣
↪'Board_of_Education_SubDistrict',
                            'County_Board_of_Education_District',␣
↪'County_Board_of_Education_SubDistrict',
                            'Education_Commission_District',␣
↪'Educational_Service_District',
                            'Educational_Service_Subdistrict',␣
↪'Regional_Office_of_Education_District',
                           ␣
↪'CommercialDataLL_Interest_in_Education_Online_In_Household')

##Print schema to examine output
df_east_sample.printSchema()
```

```
root
 |-- County: string (nullable = true)
 |-- Voters_FIPS: integer (nullable = true)
 |-- CommercialData_Education: string (nullable = true)
 |-- CommercialData_AreaMedianEducationYears: integer (nullable = true)
 |-- ElectionReturns_G08CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G10CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G12CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G14CountyTurnoutAllRegisteredVoters: string (nullable =
```

```
true)
 |-- ElectionReturns_G16CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_G18CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P08CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P10CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P12CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P14CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P16CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- ElectionReturns_P18CountyTurnoutAllRegisteredVoters: string (nullable =
true)
 |-- CommercialData_StateIncomeDecile: integer (nullable = true)
 |-- CommercialData_EstimatedHHIncome: string (nullable = true)
```

5.5 Data type inconsistency handling

[16]:
```
# replace percentage character in voter turnout columns
df_east_sample = df_east_sample.
 ↪withColumn("ElectionReturns_G08CountyTurnoutAllRegisteredVoters"
                                                            ␣
 ↪,regexp_replace('ElectionReturns_G08CountyTurnoutAllRegisteredVoters', '%',␣
 ↪''))
df_east_sample = df_east_sample.
 ↪withColumn("ElectionReturns_G10CountyTurnoutAllRegisteredVoters"
                                                            ␣
 ↪,regexp_replace('ElectionReturns_G10CountyTurnoutAllRegisteredVoters', '%',␣
 ↪''))
df_east_sample = df_east_sample.
 ↪withColumn("ElectionReturns_G12CountyTurnoutAllRegisteredVoters"
                                                            ␣
 ↪,regexp_replace('ElectionReturns_G12CountyTurnoutAllRegisteredVoters', '%',␣
 ↪''))
df_east_sample = df_east_sample.
 ↪withColumn("ElectionReturns_G14CountyTurnoutAllRegisteredVoters"
                                                            ␣
 ↪,regexp_replace('ElectionReturns_G14CountyTurnoutAllRegisteredVoters', '%',␣
 ↪''))
df_east_sample = df_east_sample.
 ↪withColumn("ElectionReturns_G16CountyTurnoutAllRegisteredVoters"
```

```
                                                                    ␣
↪,regexp_replace('ElectionReturns_G16CountyTurnoutAllRegisteredVoters', '%',␣
↪''))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_G18CountyTurnoutAllRegisteredVoters"
                                                                    ␣
↪,regexp_replace('ElectionReturns_G18CountyTurnoutAllRegisteredVoters', '%',␣
↪''))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P08CountyTurnoutAllRegisteredVoters"
                                                                    ␣
↪,regexp_replace('ElectionReturns_P08CountyTurnoutAllRegisteredVoters', '%',␣
↪''))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P10CountyTurnoutAllRegisteredVoters"
                                                                    ␣
↪,regexp_replace('ElectionReturns_P10CountyTurnoutAllRegisteredVoters', '%',␣
↪''))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P12CountyTurnoutAllRegisteredVoters"
                                                                    ␣
↪,regexp_replace('ElectionReturns_P12CountyTurnoutAllRegisteredVoters', '%',␣
↪''))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P14CountyTurnoutAllRegisteredVoters"
                                                                    ␣
↪,regexp_replace('ElectionReturns_P14CountyTurnoutAllRegisteredVoters', '%',␣
↪''))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P16CountyTurnoutAllRegisteredVoters"
                                                                    ␣
↪,regexp_replace('ElectionReturns_P16CountyTurnoutAllRegisteredVoters', '%',␣
↪''))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P18CountyTurnoutAllRegisteredVoters"
                                                                    ␣
↪,regexp_replace('ElectionReturns_P18CountyTurnoutAllRegisteredVoters', '%',␣
↪''))
```

[17]:
```
# convert string type to double for numeric columns
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_G08CountyTurnoutAllRegisteredVoters"
                                                    ,df_east_sample.
↪ElectionReturns_G08CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_G10CountyTurnoutAllRegisteredVoters"
```

```
                                                ,df_east_sample.
↪ElectionReturns_G10CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_G12CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_G12CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_G14CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_G14CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_G16CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_G16CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_G18CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_G18CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P08CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_P08CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P10CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_P10CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P12CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_P12CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P14CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_P14CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P16CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_P16CountyTurnoutAllRegisteredVoters.cast('double'))
df_east_sample = df_east_sample.
↪withColumn("ElectionReturns_P18CountyTurnoutAllRegisteredVoters"
                                                ,df_east_sample.
↪ElectionReturns_P18CountyTurnoutAllRegisteredVoters.cast('double'))
```

[18]:
```
# chech schema again
df_east_sample.printSchema()
```

```
root
 |-- County: string (nullable = true)
 |-- Voters_FIPS: integer (nullable = true)
 |-- CommercialData_Education: string (nullable = true)
 |-- CommercialData_AreaMedianEducationYears: integer (nullable = true)
 |-- ElectionReturns_G08CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_G10CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_G12CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_G14CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_G16CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_G18CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_P08CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_P10CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_P12CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_P14CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_P16CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- ElectionReturns_P18CountyTurnoutAllRegisteredVoters: double (nullable =
true)
 |-- CommercialData_StateIncomeDecile: integer (nullable = true)
 |-- CommercialData_EstimatedHHIncome: string (nullable = true)
```

5.6 Missing value imputation / drop

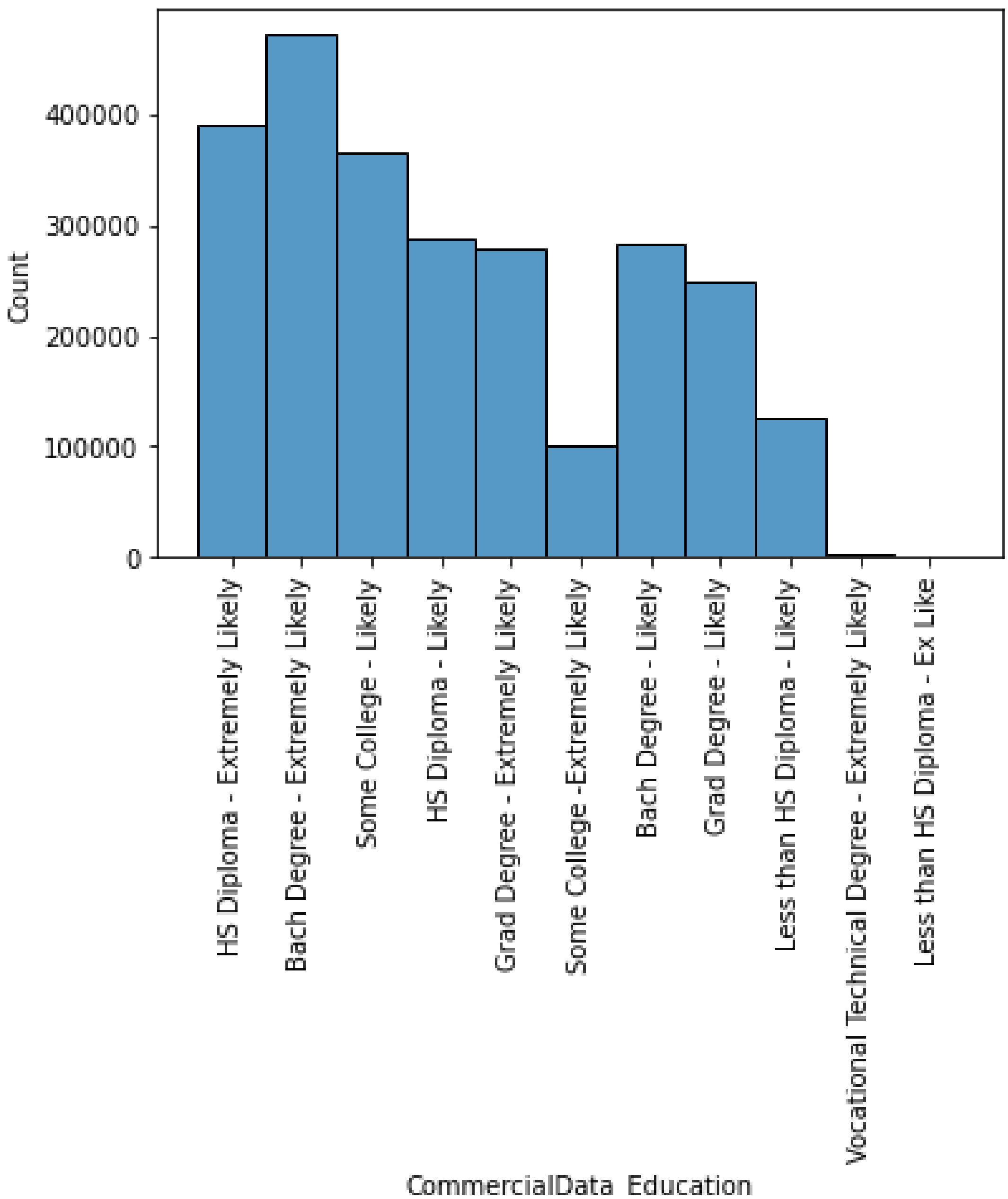
[19]:
```
# Check missing values
pd_east_sample.isnull().sum()/len(pd_east_sample)
```

[19]:
```
County                                                 0.000000
Voters_FIPS                                            0.000000
CommercialData_Education                               0.403178
CommercialData_AreaMedianEducationYears                0.038577
ElectionReturns_G08CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_G10CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_G12CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_G14CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_G16CountyTurnoutAllRegisteredVoters    0.000000
```

```
ElectionReturns_G18CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P08CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P10CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P12CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P14CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P16CountyTurnoutAllRegisteredVoters    0.000000
ElectionReturns_P18CountyTurnoutAllRegisteredVoters    0.000000
CommercialData_StateIncomeDecile                       0.038577
CommercialData_EstimatedHHIncome                       0.023909
dtype: float64
```

check the distribution of CommercialData_StateIncomeDecile to decide missing value handling method.

[20]:
```
# check the distribution of CommercialData_Education, a categorical variable
sns.histplot(pd_east_sample.CommercialData_Education)
plt.tick_params(axis='x', rotation=90)
```



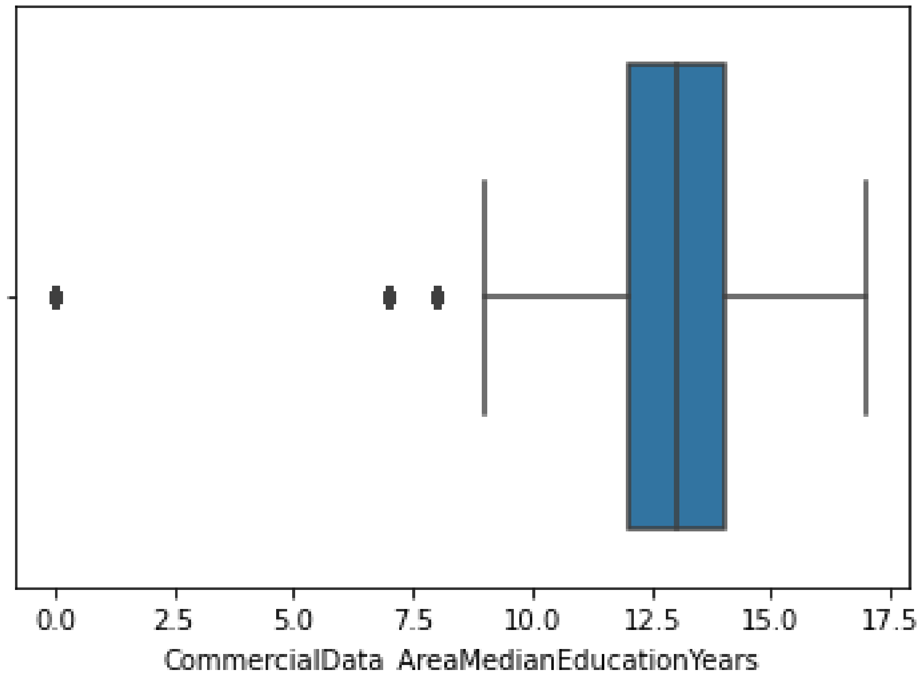
Since there's 40% data missing, we will fill them with 'Unknown'.

[21]:
```
# check the distribution of CommercialData_AreaMedianEducationYears
sns.boxplot(pd_east_sample.CommercialData_AreaMedianEducationYears)
```

```
/opt/conda/miniconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
```

```
misinterpretation.
  warnings.warn(
```

[21]: <AxesSubplot:xlabel='CommercialData_AreaMedianEducationYears'>

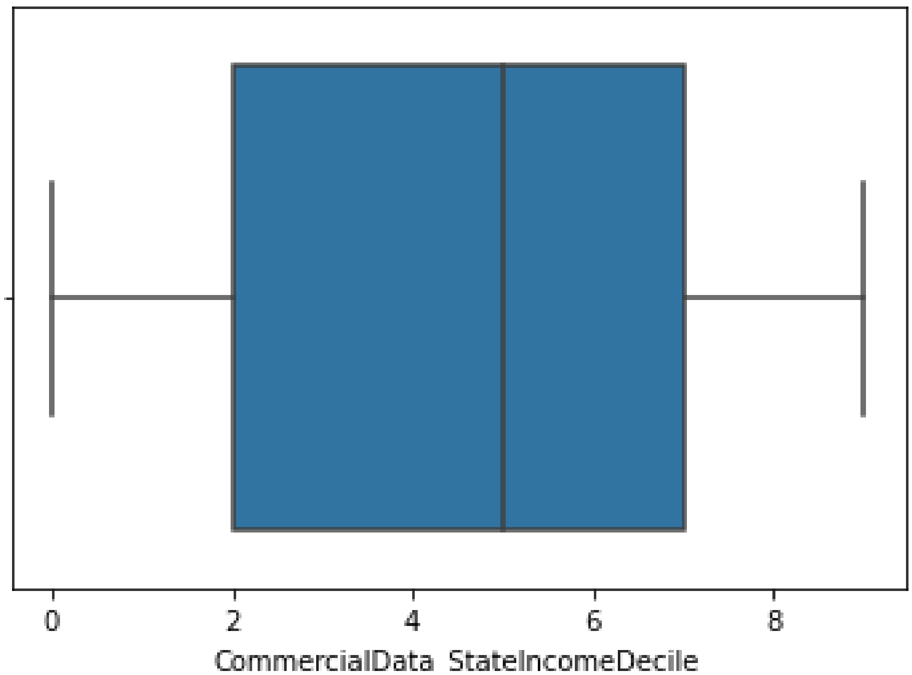


There are a few outliers, but no outlier handling is needed since it's likely not to be false data.

[22]:
```python
# check the distribution of CommercialData_StateIncomeDecile
sns.boxplot(pd_east_sample.CommercialData_StateIncomeDecile)
```

```
/opt/conda/miniconda3/lib/python3.8/site-packages/seaborn/_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```

[22]: <AxesSubplot:xlabel='CommercialData_StateIncomeDecile'>



We can fill the 3% missing values with mean.

[23]:
```
# Calculate the average education years for missing value imputation
mean_edu = pd_east_sample.CommercialData_AreaMedianEducationYears.mean()
mean_income_decile = pd_east_sample.CommercialData_StateIncomeDecile.mean()
```

[24]:
```
# Fill missing values with different methods
# fill CommercialData_Education and CommercialData_EstimatedHHIncome with␣
↪unknown to avoid introducing bias
# fill CommercialData_AreaMedianEducationYears with average education years
# fill CommercialData_EstimatedHHIncome with unknown to avoid introducing bias
df_east_sample = df_east_sample.na.fill({'CommercialData_Education':'Unknown',
                         'CommercialData_AreaMedianEducationYears': mean_edu,
                         'CommercialData_EstimatedHHIncome': 'Unknown',
                         'CommercialData_StateIncomeDecile':mean_income_decile})
```

[25]:
```
# check if successfully imputed missing values
df_east_sample.toPandas().isnull().sum()
```

[25]:
```
County                                       0
Voters_FIPS                                  0
CommercialData_Education                     0
CommercialData_AreaMedianEducationYears      0
```

```
ElectionReturns_G08CountyTurnoutAllRegisteredVoters    0
ElectionReturns_G10CountyTurnoutAllRegisteredVoters    0
ElectionReturns_G12CountyTurnoutAllRegisteredVoters    0
ElectionReturns_G14CountyTurnoutAllRegisteredVoters    0
ElectionReturns_G16CountyTurnoutAllRegisteredVoters    0
ElectionReturns_G18CountyTurnoutAllRegisteredVoters    0
ElectionReturns_P08CountyTurnoutAllRegisteredVoters    0
ElectionReturns_P10CountyTurnoutAllRegisteredVoters    0
ElectionReturns_P12CountyTurnoutAllRegisteredVoters    0
ElectionReturns_P14CountyTurnoutAllRegisteredVoters    0
ElectionReturns_P16CountyTurnoutAllRegisteredVoters    0
ElectionReturns_P18CountyTurnoutAllRegisteredVoters    0
CommercialData_StateIncomeDecile                       0
CommercialData_EstimatedHHIncome                       0
dtype: int64
```

[26]:
```
# Display our MA and NY cleaned data result with pandas dataframe
df_east_sample.toPandas().head(5)
```

[26]:
```
       County  Voters_FIPS        CommercialData_Education  \
0  BARNSTABLE            1                         Unknown
1  BARNSTABLE            1  Bach Degree - Extremely Likely
2  BARNSTABLE            1            HS Diploma - Likely
3  BARNSTABLE            1          Some College - Likely
4  BARNSTABLE            1  Bach Degree - Extremely Likely

   CommercialData_AreaMedianEducationYears  \
0                                       13
1                                       13
2                                       13
3                                       13
4                                       12

   ElectionReturns_G08CountyTurnoutAllRegisteredVoters  \
0                                               79.0
1                                               79.0
2                                               79.0
3                                               79.0
4                                               79.0

   ElectionReturns_G10CountyTurnoutAllRegisteredVoters  \
0                                               65.0
1                                               65.0
2                                               65.0
3                                               65.0
4                                               65.0
```

```
   ElectionReturns_G12CountyTurnoutAllRegisteredVoters  \
0                                               79.0
1                                               79.0
2                                               79.0
3                                               79.0
4                                               79.0

   ElectionReturns_G14CountyTurnoutAllRegisteredVoters  \
0                                               59.0
1                                               59.0
2                                               59.0
3                                               59.0
4                                               59.0

   ElectionReturns_G16CountyTurnoutAllRegisteredVoters  \
0                                               79.0
1                                               79.0
2                                               79.0
3                                               79.0
4                                               79.0

   ElectionReturns_G18CountyTurnoutAllRegisteredVoters  \
0                                               68.0
1                                               68.0
2                                               68.0
3                                               68.0
4                                               68.0

   ElectionReturns_P08CountyTurnoutAllRegisteredVoters  \
0                                               18.0
1                                               18.0
2                                               18.0
3                                               18.0
4                                               18.0

   ElectionReturns_P10CountyTurnoutAllRegisteredVoters  \
0                                               26.0
1                                               26.0
2                                               26.0
3                                               26.0
4                                               26.0

   ElectionReturns_P12CountyTurnoutAllRegisteredVoters  \
0                                               18.0
1                                               18.0
2                                               18.0
```

```
3                                              18.0
4                                              18.0

   ElectionReturns_P14CountyTurnoutAllRegisteredVoters  \
0                                              22.0
1                                              22.0
2                                              22.0
3                                              22.0
4                                              22.0

   ElectionReturns_P16CountyTurnoutAllRegisteredVoters  \
0                                              19.0
1                                              19.0
2                                              19.0
3                                              19.0
4                                              19.0

   ElectionReturns_P18CountyTurnoutAllRegisteredVoters  \
0                                              27.0
1                                              27.0
2                                              27.0
3                                              27.0
4                                              27.0

   CommercialData_StateIncomeDecile CommercialData_EstimatedHHIncome
0                                 4                  $200000-249999
1                                 3                  $175000-199999
2                                 4                    $50000-74999
3                                 4                  $175000-199999
4                                 3                    $75000-99999
```

[27]:
```
pd_east_sample.head()
```

[27]:
```
       County  Voters_FIPS        CommercialData_Education  \
0  BARNSTABLE            1   HS Diploma - Extremely Likely
1  BARNSTABLE            1                            None
2  BARNSTABLE            1                            None
3  BARNSTABLE            1  Bach Degree - Extremely Likely
4  BARNSTABLE            1           Some College - Likely

   CommercialData_AreaMedianEducationYears  \
0                                     12.0
1                                     12.0
2                                     14.0
3                                     13.0
4                                     13.0
```

```
  ElectionReturns_G08CountyTurnoutAllRegisteredVoters  \
0                                                 79%
1                                                 79%
2                                                 79%
3                                                 79%
4                                                 79%

  ElectionReturns_G10CountyTurnoutAllRegisteredVoters  \
0                                                 65%
1                                                 65%
2                                                 65%
3                                                 65%
4                                                 65%

  ElectionReturns_G12CountyTurnoutAllRegisteredVoters  \
0                                                 79%
1                                                 79%
2                                                 79%
3                                                 79%
4                                                 79%

  ElectionReturns_G14CountyTurnoutAllRegisteredVoters  \
0                                                 59%
1                                                 59%
2                                                 59%
3                                                 59%
4                                                 59%

  ElectionReturns_G16CountyTurnoutAllRegisteredVoters  \
0                                                 79%
1                                                 79%
2                                                 79%
3                                                 79%
4                                                 79%

  ElectionReturns_G18CountyTurnoutAllRegisteredVoters  \
0                                                 68%
1                                                 68%
2                                                 68%
3                                                 68%
4                                                 68%

  ElectionReturns_P08CountyTurnoutAllRegisteredVoters  \
0                                                 18%
1                                                 18%
2                                                 18%
3                                                 18%
```

```
4                                                18%

  ElectionReturns_P10CountyTurnoutAllRegisteredVoters  \
0                                                26%
1                                                26%
2                                                26%
3                                                26%
4                                                26%

  ElectionReturns_P12CountyTurnoutAllRegisteredVoters  \
0                                                18%
1                                                18%
2                                                18%
3                                                18%
4                                                18%

  ElectionReturns_P14CountyTurnoutAllRegisteredVoters  \
0                                                22%
1                                                22%
2                                                22%
3                                                22%
4                                                22%

  ElectionReturns_P16CountyTurnoutAllRegisteredVoters  \
0                                                19%
1                                                19%
2                                                19%
3                                                19%
4                                                19%

  ElectionReturns_P18CountyTurnoutAllRegisteredVoters  \
0                                                27%
1                                                27%
2                                                27%
3                                                27%
4                                                27%

   CommercialData_StateIncomeDecile CommercialData_EstimatedHHIncome
0                               2.0                      $50000-74999
1                               3.0                      $75000-99999
2                               6.0                    $125000-149999
3                               5.0                    $125000-149999
4                               3.0                    $200000-249999
```

5.7 Data Cleansing on Education dataframe

[28]:
```
df_edu.toPandas().isnull().sum()
```

[28]:
```
GEO_ID             0
NAME               0
S1501_C01_001E     0
S1501_C01_001M     0
S1501_C01_002E     0
                  ..
S1501_C06_062M    77
S1501_C06_063E    77
S1501_C06_063M    77
S1501_C06_064E    77
S1501_C06_064M    77
Length: 770, dtype: int64
```

[29]:
```
# get columns names with data type inconsistentency problem
cols = []
for _col in df_edu.dtypes:
    if _col[1] == 'string':
        cols.append(_col[0])
```

[30]:
```
# convert data type to float for all numeric columns
cols = cols[2:]  # Exclude id and name column
for col_name in cols:
    df_edu = df_edu.withColumn(col_name, col(col_name).cast('float'))
```

[31]:
```
# Check missing values
df_edu.toPandas().isnull().sum()/len(df_edu.toPandas())
```

[31]:
```
GEO_ID            0.0
NAME              0.0
S1501_C01_001E    0.0
S1501_C01_001M    0.0
S1501_C01_002E    0.0
                 …
S1501_C06_062M    1.0
S1501_C06_063E    1.0
S1501_C06_063M    1.0
S1501_C06_064E    1.0
S1501_C06_064M    1.0
Length: 770, dtype: float64
```

[32]:
```
# Display one of the columns with too many missing values
df_edu.select("S1501_C01_052M").show()
```

```
+--------------+
|S1501_C01_052M|
+--------------+
|          94.0|
|          null|
|          null|
|         112.0|
|          null|
|          71.0|
|          null|
|          null|
|          null|
|         200.0|
|          null|
|          null|
|          null|
|          null|
|          null|
|          33.0|
|          null|
|          null|
|          64.0|
|          44.0|
+--------------+
only showing top 20 rows
```

[33]:
```
# convert to pandas dataframe then drop columns with too many empty values
df_edu = df_edu.toPandas().dropna(axis='columns', thresh = int(0.80 * df_edu.
 ↪count()))

# Check missing values now
df_edu.isnull().sum().max()
```

[33]: 2

[34]:
```
# Since there're only the maximum missing values per column is 2,
# we will fill the rest of missing values with mean
df_edu.fillna(df_edu.mean(), inplace=True)

# Confirm the missing values again
df_edu.isnull().sum().max()
```

[34]: 0

[35]:
```python
# convert back to Spark dataframe
df_edu = spark.createDataFrame(df_edu)
```

5.8 Merge with Education Dataset from US Census Bureau

Since the FIPS code in the NY_MA voting dataset only has two digits, we can't directly merge on the FIPS code. We will merge the two datasets using County name as a primary key, and FIPS code as a secondary key.

[36]:
```python
# extract county names from the Education dataframe using regex
df_edu = df_edu.withColumn("County", regexp_extract(col('NAME'), '(.
↪+)(\s)(County)(.)', 1))
```

[37]:
```python
# Convert county name to upper case to match with original dataset
df_edu = df_edu.withColumn("County", upper(col('County')))
```

[38]:
```python
# Slice the last two digits of GEO_ID to match with FIPS code
df_edu = df_edu.withColumn("Voters_FIPS", substring('GEO_ID', 12,3))

# Cast the sliced string back to int to match with the NY_MA FIPS code format
df_edu = df_edu.withColumn("Voters_FIPS", col('Voters_FIPS').
↪cast(IntegerType()))
df_east_sample.withColumn("Voters_FIPS", col('Voters_FIPS').cast(IntegerType()))
```

[38]:
```
DataFrame[County: string, Voters_FIPS: int, CommercialData_Education: string,
CommercialData_AreaMedianEducationYears: int,
ElectionReturns_G08CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_G10CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_G12CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_G14CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_G16CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_G18CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_P08CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_P10CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_P12CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_P14CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_P16CountyTurnoutAllRegisteredVoters: double,
ElectionReturns_P18CountyTurnoutAllRegisteredVoters: double,
CommercialData_StateIncomeDecile: int, CommercialData_EstimatedHHIncome: string]
```

[39]:
```python
# check if succeed
df_edu.toPandas().head(5)
```

[39]:
```
           GEO_ID                               NAME  S1501_C01_001E  \
0  0500000US25001  Barnstable County, Massachusetts           14900
1  0500000US25003   Berkshire County, Massachusetts           11936
2  0500000US25005     Bristol County, Massachusetts           50816
3  0500000US25007       Dukes County, Massachusetts            1201
4  0500000US25009       Essex County, Massachusetts           72181

   S1501_C01_001M  S1501_C01_002E  S1501_C01_002M  S1501_C01_003E  \
0             172            1934             327            5008
1             166            1190             208            3390
2             104            6099             615           18257
3             183             265             168             280
4              83            9319             689           22524

   S1501_C01_003M  S1501_C01_004E  S1501_C01_004M  …  S1501_C06_055E  \
0             569            5134             593  …            14.1
1             368            6201             396  …            22.4
2             938           20117             883  …            23.6
3             153             535             223  …            17.3
4            1106           28294            1219  …            27.7

   S1501_C06_055M  S1501_C06_056E  S1501_C06_056M  S1501_C06_057E  \
0             3.9            10.0             1.6             8.6
1             5.2            12.0             2.1             9.3
2             2.1            12.5             1.3            10.5
3            23.5            19.8            14.0             6.3
4             2.4            16.0             1.4             9.7

   S1501_C06_057M  S1501_C06_058E  S1501_C06_058M      County  Voters_FIPS
0             1.5             4.5             0.8  BARNSTABLE          1.0
1             1.7             4.2             0.9   BERKSHIRE          3.0
2             1.0             4.0             0.6     BRISTOL          5.0
3             4.4             2.8             1.8       DUKES          7.0
4             0.9             4.2             0.5       ESSEX          9.0

[5 rows x 607 columns]
```

[40]:
```
# Join NY_MA voting dataset with education dataset on county and GEO_ID/FIPS␣
↪code
df_all = df_east_sample.join(df_edu, on = ["County", "Voters_FIPS"], how =␣
↪"left_outer")
```

The below blocks can be uncommented for either of the data sets if we wish to write them to an external file for ease of future use

[ ]:
```
# ## Write to .csv for dashboard
# df_sample = df_all.sample(fraction = 0.1)
```

```
# df_sample.write.csv("gs://project_bucket_real/notebooks/jupyter/data/
↪dashboard_data.csv")
```

[ ]:
```
# ## Write to parquet
# df_all.write.parquet("gs://project_bucket_real/notebooks/jupyter/data/
↪final_df_0429.parquet")
```

6 Exploratory Data Analysis

For this part, we mainly focus on the following questions: 1. What has been the trend in voter turnout over the past few years? 2. Does education level have any impact on voting turnout? 3. Is there disparity in turnout between primary and general election for different education levels? 4. What other factors, such as income disparity impact on voting, could confound education as a factor?

As stated in the data cleansing section, we'll continue to use a subset of the MA + NY voter turnout data with the full set of US Census educational attainment data. Most of the analysis will use county-level information from the voter turnout data set, so we only need to use a subset that is large enough that there is a row for each county. At that point, increasing the amount of voter turnout data used (in terms of number of rows) won't add additional information since this increases only voter-level information, not county-level information. Thus, we can perform EDA quickly and efficiently, without loss of information.

The one case where the above assumption does not hold is in our initial EDA that uses voter-level educational information from the voter turnout data set. However, the sampled voter turnout data is large enough for us to showcase the issues with trying to use the educational information available in the MA and NY voter turnout data sets. The issues we will point out persist regardless of the sampled size of the voter turnout data set, and motivate why we need to use the educational information provided by the full US Census educational attainment data set.

6.1 Convert voter-level data to county-level

The above df has all the information we need, but each row is for an individual voter. I.e., it is a voter-level data frame. So if we try to describe or aggregate most of the columns, which contain county-level data, then the statistics will be inappropriately weighted by the number of voters in that county. We need to also create a county-level data frame.

[2]:
```
## Load data frame
try:
    df = df_sample
except:
    df = spark.read.parquet("gs://project_bucket_real/notebooks/jupyter/data/
↪final_df_0429.parquet")
```

[3]:
```
df.groupBy('County', 'CommercialData_Education').count().orderBy(col('count').
↪desc()).show()
```

```
[Stage 1:============================>                            (1 + 1) / 2]

+-----------+-----------------------+------+
|     County|CommercialData_Education| count|
+-----------+-----------------------+------+
|      KINGS|                Unknown|210179|
|   NEW YORK|                Unknown|158768|
|     QUEENS|                Unknown|152236|
|    SUFFOLK|                Unknown|151329|
|      BRONX|                Unknown|119854|
|     NASSAU|                Unknown| 95096|
|  MIDDLESEX|                Unknown| 88722|
|WESTCHESTER|                Unknown| 63403|
|       ERIE|                Unknown| 52820|
|      ESSEX|                Unknown| 48807|
|  WORCESTER|                Unknown| 44415|
|     MONROE|                Unknown| 42251|
|    SUFFOLK|    Bach Degree - Ext…| 38978|
|    NORFOLK|                Unknown| 38833|
|    SUFFOLK|    HS Diploma - Extr…| 33799|
|  MIDDLESEX|    Bach Degree - Ext…| 32345|
|   RICHMOND|                Unknown| 32229|
|    SUFFOLK|    Some College - Li…| 31817|
|    HAMPDEN|                Unknown| 30928|
|     NASSAU|    Bach Degree - Ext…| 30700|
+-----------+-----------------------+------+
only showing top 20 rows
```

[4]:
```python
df.groupBy('County', 'CommercialData_EstimatedHHIncome').count().
↪orderBy(col('count').desc()).show()
```

```
[Stage 4:>                                                      (0 + 2) / 2]

+---------+--------------------------------+-----+
|   County|CommercialData_EstimatedHHIncome|count|
+---------+--------------------------------+-----+
|    KINGS|                    $50000-74999|92595|
|   QUEENS|                    $75000-99999|74702|
|   QUEENS|                    $50000-74999|73364|
| NEW YORK|                  $200000-249999|70026|
|  SUFFOLK|                    $75000-99999|62371|
|  SUFFOLK|                  $100000-124999|62042|
|    KINGS|                    $75000-99999|61573|
|  SUFFOLK|                  $125000-149999|49061|
|    KINGS|                    $35000-49999|46181|
|   NASSAU|                  $125000-149999|43440|
|  SUFFOLK|                    $50000-74999|42942|
```

```
|    BRONX|                        $35000-49999|41560|
|   QUEENS|                      $100000-124999|40831|
|MIDDLESEX|                      $100000-124999|40651|
|    BRONX|                        $50000-74999|40596|
|   NASSAU|                      $100000-124999|40536|
|MIDDLESEX|                      $125000-149999|39443|
|     ERIE|                        $50000-74999|35571|
|    BRONX|                        $25000-34999|33177|
|     ERIE|                        $75000-99999|33082|
+---------+------------------------------+-----+
only showing top 20 rows
```

[5]:
```
county_level_df = df.dropDuplicates(['County'])
```

[6]:
```
county_level_df.toPandas().head(5)
```

```
22/05/02 00:13:31 WARN org.apache.spark.sql.catalyst.util.package: Truncated the
string representation of a plan since it was too large. This behavior can be
adjusted by setting 'spark.sql.debug.maxToStringFields'.
```

[6]:
```
       County  Voters_FIPS CommercialData_Education  \
0    ALLEGANY            3     Grad Degree - Likely
1  BARNSTABLE            1                  Unknown
2     BRISTOL            5     Bach Degree - Likely
3       BRONX            5                  Unknown
4      BROOME            7                  Unknown

  CommercialData_AreaMedianEducationYears  \
0                                      12
1                                      13
2                                      12
3                                      12
4                                      12

  ElectionReturns_G08CountyTurnoutAllRegisteredVoters  \
0                                               64.0
1                                               79.0
2                                               71.0
3                                               54.0
4                                               69.0

  ElectionReturns_G10CountyTurnoutAllRegisteredVoters  \
0                                               48.0
1                                               65.0
2                                               50.0
```

```
3                                              26.0
4                                              50.0

   ElectionReturns_G12CountyTurnoutAllRegisteredVoters  \
0                                              64.0
1                                              79.0
2                                              69.0
3                                              53.0
4                                              63.0

   ElectionReturns_G14CountyTurnoutAllRegisteredVoters  \
0                                              47.0
1                                              59.0
2                                              43.0
3                                              20.0
4                                              43.0

   ElectionReturns_G16CountyTurnoutAllRegisteredVoters  \
0                                              70.0
1                                              79.0
2                                              70.0
3                                              52.0
4                                              66.0

   ElectionReturns_G18CountyTurnoutAllRegisteredVoters  …  S1501_C06_054E  \
0                                              62.0    …            35.0
1                                              68.0    …            20.7
2                                              58.0    …            17.8
3                                              38.0    …            16.1
4                                              62.0    …            31.7

   S1501_C06_054M  S1501_C06_055E  S1501_C06_055M  S1501_C06_056E  \
0            23.2            31.3             6.3            18.5
1             6.1            14.1             3.9            10.0
2             3.2            23.6             2.1            12.5
3             0.7            43.0             1.3            29.1
4             9.6            32.2             4.5            16.3

   S1501_C06_056M  S1501_C06_057E S1501_C06_057M S1501_C06_058E S1501_C06_058M
0             3.1            14.2            2.4            5.4            2.1
1             1.6             8.6            1.5            4.5            0.8
2             1.3            10.5            1.0            4.0            0.6
3             1.4            21.3            1.0            9.6            0.9
4             2.1            14.6            2.0            5.6            1.0

[5 rows x 623 columns]
```

[7]:
```
county_level_educations = df.groupBy('County', 'CommercialData_Education').
    ↪count().collect()
county_level_educations_dict = defaultdict(dict)
for row in county_level_educations:
    ␣
    ↪county_level_educations_dict[row['County']][row['CommercialData_Education']]␣
    ↪= row['count']
```

[8]:
```
education_level_columns = [
    'Unknown',
    'Grad Degree - Likely',
    'Grad Degree - Extremely Likely',
    'Vocational Technical Degree - Extremely Likely',
    'Bach Degree - Extremely Likely',
    'Less than HS Diploma - Ex Like',
    'HS Diploma - Extremely Likely',
    'Some College - Likely',
    'Some College -Extremely Likely',
    'HS Diploma - Likely',
    'Bach Degree - Likely',
    'Less than HS Diploma - Likely'
]
data = []
for county in county_level_educations_dict.keys():
    row = [county]
    for education_level_column in education_level_columns:
        if education_level_column in county_level_educations_dict[county]:
            row.
    ↪append(county_level_educations_dict[county][education_level_column])
        else:
            row.append(0)
    data.append(row)
```

[9]:
```
columns = ["County"] + education_level_columns
county_level_education_df = spark.createDataFrame(data).toDF(*columns)
```

[10]:
```
county_level_education_df.toPandas().head()
```

[10]:

	County	Unknown	Grad Degree - Likely	Grad Degree - Extremely Likely	\
0	ONTARIO	5977	1092	1526	
1	CHENANGO	2304	243	429	
2	HAMPSHIRE	8991	1933	2551	
3	HERKIMER	2940	342	578	
4	CHEMUNG	3903	533	1017	

```
   Vocational Technical Degree - Extremely Likely  \
0                                              20
1                                              15
2                                              21
3                                              19
4                                              22

   Bach Degree - Extremely Likely  Less than HS Diploma - Ex Like  \
0                            2640                               8
1                             846                               2
2                            3468                               4
3                            1393                               8
4                            1604                               5

   HS Diploma - Extremely Likely  Some College - Likely  \
0                           2336                   2159
1                           1380                    701
2                           2493                   2323
3                           1643                   1109
4                           2044                   1483

   Some College -Extremely Likely  HS Diploma - Likely  Bach Degree - Likely  \
0                             696                 1212                  1050
1                             338                  864                   199
2                             819                 1398                  1517
3                             485                  971                   268
4                             562                  960                   449

   Less than HS Diploma - Likely
0                            441
1                            337
2                            430
3                            316
4                            329
```

[11]:
```
county_level_df = county_level_education_df.join(county_level_df, on = "County")
```

[12]:
```
county_level_df = county_level_df.drop('CommercialData_Education')
```

[13]:
```
county_level_df.toPandas().head()
```

[13]:
```
      County  Unknown  Grad Degree - Likely  Grad Degree - Extremely Likely  \
0    ONTARIO     5977                  1092                            1526
1   CHENANGO     2304                   243                             429
2  HAMPSHIRE     8991                  1933                            2551
```

```
3   HERKIMER     2940                    342                                578
4    CHEMUNG     3903                    533                               1017

   Vocational Technical Degree - Extremely Likely  \
0                                              20
1                                              15
2                                              21
3                                              19
4                                              22

   Bach Degree - Extremely Likely  Less than HS Diploma - Ex Like  \
0                            2640                               8
1                             846                               2
2                            3468                               4
3                            1393                               8
4                            1604                               5

   HS Diploma - Extremely Likely  Some College - Likely  \
0                           2336                   2159
1                           1380                    701
2                           2493                   2323
3                           1643                   1109
4                           2044                   1483

   Some College -Extremely Likely  …  S1501_C06_054E  S1501_C06_054M  \
0                             696  …            23.3             7.1
1                             338  …            16.1             9.2
2                             819  …            47.4             7.3
3                             485  …             8.9             8.1
4                             562  …            28.2            12.1

   S1501_C06_055E  S1501_C06_055M  S1501_C06_056E  S1501_C06_056M  \
0            20.6             5.4            15.4             3.3
1            24.6             5.9            15.9             2.8
2            19.8             6.2            11.0             2.9
3            25.3             6.7            16.9             2.8
4            39.5             7.8            17.3             3.2

   S1501_C06_057E  S1501_C06_057M  S1501_C06_058E  S1501_C06_058M
0             7.2             1.7             2.0             0.7
1            12.2             2.6             3.9             1.8
2            10.2             2.1             5.0             1.0
3            10.3             2.0             5.3             2.0
4            11.0             2.1             4.5             2.1

[5 rows x 634 columns]
```

```
[14]: county_level_income_levels = df.groupBy('County',␣
       ↪'CommercialData_EstimatedHHIncome').count().collect()
      county_level_income_levels_dict = defaultdict(dict)
      for row in county_level_income_levels:
          ␣
       ↪county_level_income_levels_dict[row['County']][row['CommercialData_EstimatedHHIncome']]␣
       ↪= row['count']
```

```
[15]: income_level_columns = [
          '$150000-174999', '$100000-124999', '$75000-99999',
             '$125000-149999', '$50000-74999', '$175000-199999', '$35000-49999',
             '$200000-249999', '$25000-34999', '$1000-14999', '$15000-24999',
             '$250000+'
      ]

      data = []
      for county in county_level_income_levels_dict.keys():
          row = [county]
          for income_level_column in income_level_columns:
              if income_level_column in county_level_income_levels_dict[county]:
                  row.
       ↪append(county_level_income_levels_dict[county][income_level_column])
              else:
                  row.append(0)
          data.append(row)
```

```
[16]: columns = ["County"] + income_level_columns
      county_level_income_df = spark.createDataFrame(data).toDF(*columns)
```

```
[17]: county_level_income_df.toPandas().head()
```

```
[17]:      County  $150000-174999  $100000-124999  $75000-99999  $125000-149999  \
      0  RICHMOND            4255           17621         14495           11085
      1     BRONX            2065            8789         19230            7291
      2  CHENANGO              64             405          1271             315
      3      ERIE            4512           20144         33082           13063
      4    OTSEGO             159             799          1633             480

         $50000-74999  $175000-199999  $35000-49999  $200000-249999  $25000-34999  \
      0          9448            4082          4186            4403          1690
      1         40596            1985         41560            1739         33177
      2          3044              67           915              64           431
      3         35571            3878         15854            3402         10287
      4          3060             170           781             112           470
```

```
   $1000-14999  $15000-24999  $250000+
0         2043          1374      4505
1        13023         27632      1897
2          345           428        48
3         6312          7454      4452
4          330           359       178
```

[18]:
```
county_level_df = county_level_income_df.join(county_level_df, on = "County")
```

[19]:
```
county_level_df = county_level_df.drop('CommercialData_EstimatedHHIncome')
```

[20]:
```
county_level_df.toPandas().head()
```

[20]:
```
      County  $150000-174999  $100000-124999  $75000-99999  $125000-149999  \
0    ONTARIO             426            2488          4941            2132
1   CHENANGO              64             405          1271             315
2  HAMPSHIRE            1339            4823          7149            2497
3   HERKIMER             115             590          1764             431
4    CHEMUNG             121            1234          2724             678

   $50000-74999  $175000-199999  $35000-49999  $200000-249999  $25000-34999  \
0          3904             525          1506             557           786
1          3044              67           915              64           431
2          2865             876          1490             844           772
3          3732              82          1280              94           661
4          3903             158          1414             164          1027

   …  S1501_C06_054E  S1501_C06_054M  S1501_C06_055E  S1501_C06_055M  \
0  …            23.3             7.1            20.6             5.4
1  …            16.1             9.2            24.6             5.9
2  …            47.4             7.3            19.8             6.2
3  …             8.9             8.1            25.3             6.7
4  …            28.2            12.1            39.5             7.8

   S1501_C06_056E  S1501_C06_056M  S1501_C06_057E  S1501_C06_057M  \
0            15.4             3.3             7.2             1.7
1            15.9             2.8            12.2             2.6
2            11.0             2.9            10.2             2.1
3            16.9             2.8            10.3             2.0
4            17.3             3.2            11.0             2.1

   S1501_C06_058E  S1501_C06_058M
0             2.0             0.7
1             3.9             1.8
2             5.0             1.0
```

```
3              5.3             2.0
4              4.5             2.1

[5 rows x 645 columns]
```

If we take a look at county-level turnout for the most recent general election (2018), it appears average turnout across MA & NY counties was 60% with min-max values of 38% and 70%

[21]:
```
county_level_df.
 ↪describe(['ElectionReturns_G18CountyTurnoutAllRegisteredVoters']).show()
```

```
+-------+---------------------------------------------------+
|summary|ElectionReturns_G18CountyTurnoutAllRegisteredVoters|
+-------+---------------------------------------------------+
|  count|                                                 73|
|   mean|                                  59.945205479452056|
| stddev|                                   6.195631101740841|
|    min|                                               38.0|
|    max|                                               70.0|
+-------+---------------------------------------------------+
```

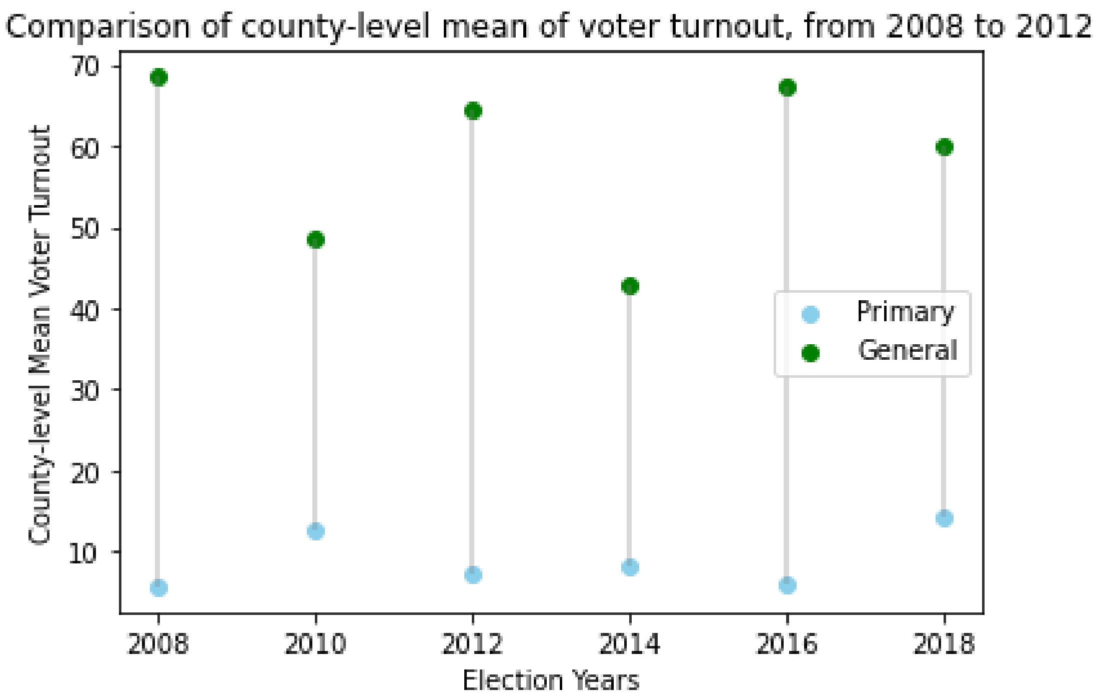
6.2 Explore voter turnout

Let's see how voter turnout has changed over the past 6 elections and if there is a notable difference in turnout between general and primary elections.

[22]:
```
## Let's look at county level turnout over the past 6 elections
G_Turnouts = [_col for _col in county_level_df.columns if "_G" in _col]
P_Turnouts = [_col for _col in county_level_df.columns if "_P" in _col]

G_avg_turnout = [county_level_df.agg({_col: 'avg'}).collect()[0][0] for _col in␣
 ↪G_Turnouts]
P_avg_turnout = [county_level_df.agg({_col: 'avg'}).collect()[0][0] for _col in␣
 ↪P_Turnouts]
```

[23]:
```
years = ["2008", "2010", "2012", "2014", "2016", "2018"]
temp_df = pd.DataFrame({'years': years, 'G_Avg_Turnout' : G_avg_turnout,␣
 ↪'P_Avg_Turnout' : P_avg_turnout})

# Make plot
plt.vlines(x=temp_df['years'], ymin=temp_df['P_Avg_Turnout'],␣
 ↪ymax=temp_df['G_Avg_Turnout'], color='grey', alpha=0.4)
plt.scatter(temp_df['years'], temp_df['P_Avg_Turnout'], color='skyblue',␣
 ↪alpha=1, label='Primary')
```

```
plt.scatter(temp_df['years'], temp_df['G_Avg_Turnout'], color='green', alpha=1,␣
↪label='General')
plt.legend()

# Add title and axis names
plt.title("Comparison of county-level mean of voter turnout, from 2008 to 2012")
plt.xlabel('Election Years')
plt.ylabel('County-level Mean Voter Turnout');
```



Wow! The trends aren't surprising, but perhaps the magnitudes of them are. As we expected, voter turnout is much higher for general elections than primary elections and voter turnout is higher when presidential candidates are involved. We also see that 2018 had more active voter participation relative to all other Primary election years and 2010 and 2014 General election years.

Let's create three additional columns that average turnout across: 1. The past 6 General elections 2. The past 6 Primary elections 3. The past 3 General elections that include Presidential election (2008, 2012, 2016)

[24]:
```
county_level_df = county_level_df.withColumn("G_AvgTurnout",␣
↪(col('ElectionReturns_G08CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_G10CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_G12CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_G14CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_G16CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_G18CountyTurnoutAllRegisteredVoters'))/6)
```

```
county_level_df = county_level_df.withColumn("P_AvgTurnout",␣
↪(col('ElectionReturns_P08CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_P10CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_P12CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_P14CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_P16CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_P18CountyTurnoutAllRegisteredVoters'))/6)

county_level_df = county_level_df.withColumn("G_AvgTurnout_Pres",␣
↪(col('ElectionReturns_G08CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_G12CountyTurnoutAllRegisteredVoters')\
        +col('ElectionReturns_G16CountyTurnoutAllRegisteredVoters'))/3)
```

Since the county-level results have a much smaller amount of rows compared to the voter-level data frame, we can convert to Pandas for ease of plotting.

[25]:
```
pandas_county_level_df = county_level_df.toPandas()
```

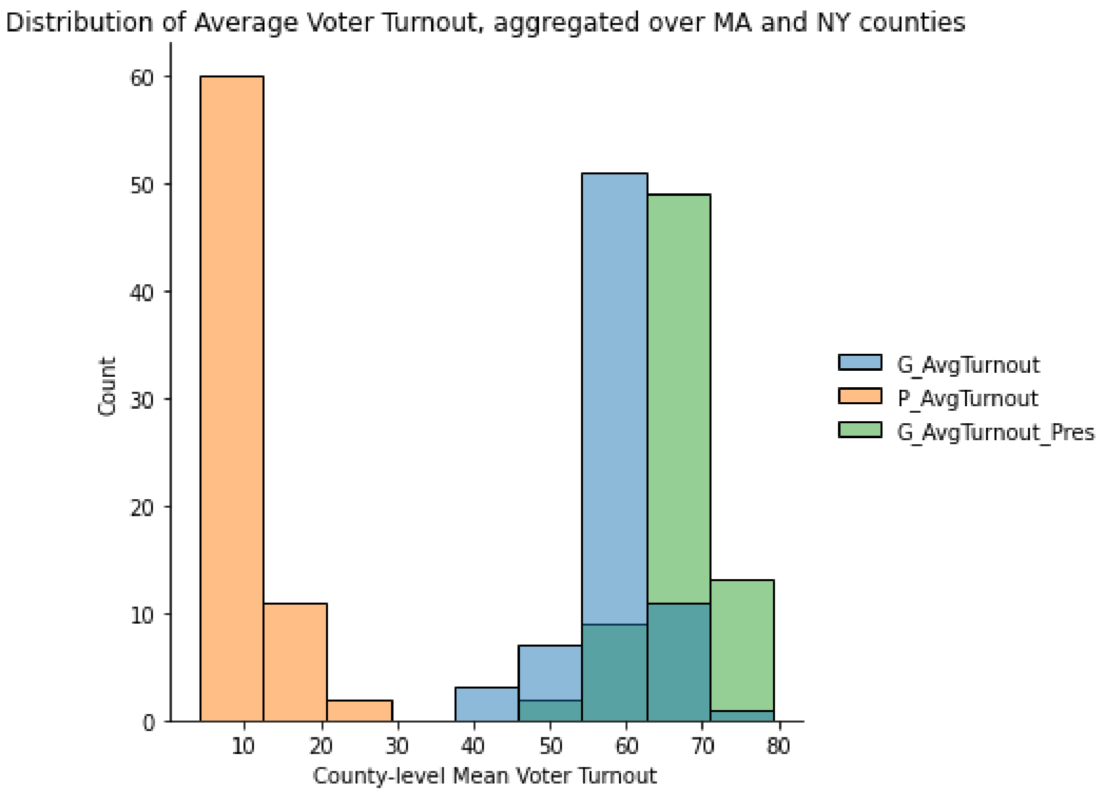
If we take a look at average turnout, the mean, min, and max are all aligned with the results we observed in the lollipop plot from earlier.

We also plot the distribution for each average turnout class, further confirming the same trends.

[26]:
```
county_level_df.describe(['G_AvgTurnout', 'P_AvgTurnout', 'G_AvgTurnout_Pres']).
↪show()
```

```
+-------+-----------------+------------------+-----------------+
|summary|     G_AvgTurnout|      P_AvgTurnout|G_AvgTurnout_Pres|
+-------+-----------------+------------------+-----------------+
|  count|               73|                73|               73|
|   mean|58.61415525114155| 9.079908675799086|66.81735159817353|
| stddev|5.775565596289581| 4.169731242360754|5.399485885417445|
|    min|             40.5|               4.0|             53.0|
|    max|             71.5|21.666666666666668|79.33333333333333|
+-------+-----------------+------------------+-----------------+
```

[27]:
```
sns.displot(pandas_county_level_df[['G_AvgTurnout', 'P_AvgTurnout',␣
↪'G_AvgTurnout_Pres']])

# Add title and axis names
plt.title("Distribution of Average Voter Turnout, aggregated over MA and NY␣
↪counties")
plt.ylabel('Count')
plt.xlabel('County-level Mean Voter Turnout');
```



Average turnout over all General elections follows a Normal distribution, but average turnout over either all Primary elections or over the 2008, 2012, and 2016 General elections are skewed and not bell-shaped. Furthermore, the distributions are all centered at different magnitudes of voter turnout and they all have wide turnout ranges of 30%.

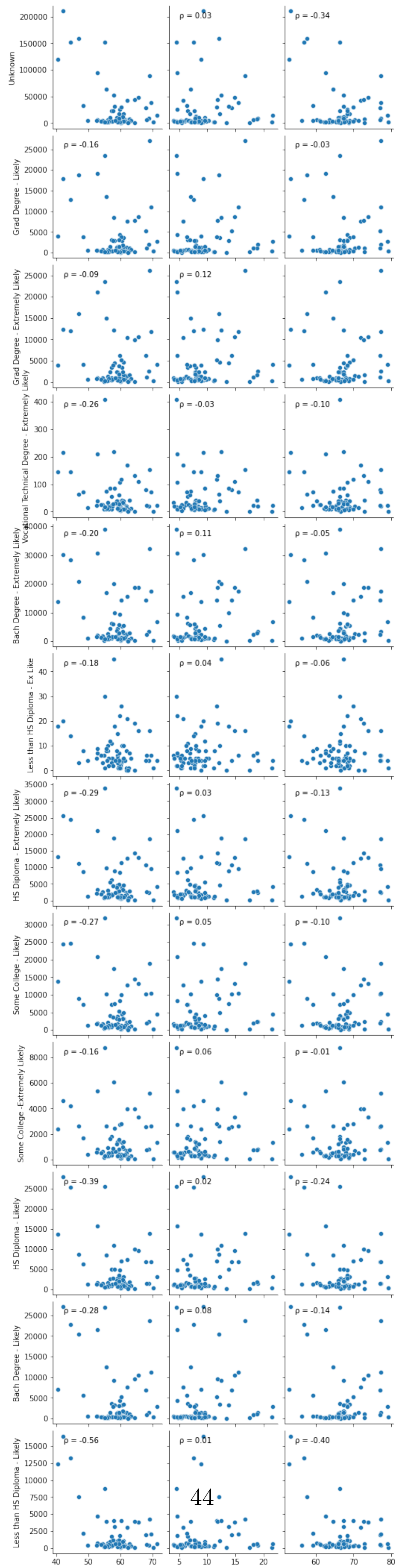
6.3 Education & voter turnout

Let's explore the effects of education, such as whether it may explain the wide ranges or discrepancies in turnout between Primary, General, and Presidential election cycles.

[28]:
```
from scipy.stats import pearsonr
## Credit: https://stackoverflow.com/questions/50832204/
↪show-correlation-values-in-pairplot-using-seaborn-in-python
def corrfunc(x, y, ax=None, **kws):
    """Plot the correlation coefficient in the top left hand corner of a plot.
↪"""
    r, _ = pearsonr(x, y)
    ax = ax or plt.gca()
    ax.annotate(f'  = {r:.2f}', xy=(.1, .9), xycoords=ax.transAxes)
```

[29]:
```
g = sns.pairplot(data=pandas_county_level_df,
            x_vars=['G_AvgTurnout', 'P_AvgTurnout', 'G_AvgTurnout_Pres'],
```

```
            y_vars=education_level_columns)
g.map_upper(corrfunc)
g.map_diag(corrfunc)
g.map_lower(corrfunc)
plt.show()
```


Unknown
Grad Degree - Likely
Grad Degree - Extremely Likely
Vocational Technical Degree - Extremely Likely
Bach Degree - Extremely Likely
Less than HS Diploma - Ex Like
HS Diploma - Extremely Likely
Some College - Likely
Some College -Extremely Likely
HS Diploma - Likely
Bach Degree - Likely
Less than HS Diploma - Likely
G_AvgTurnout
P_AvgTurnout
G_AvgTurnout_Pres
ρ = 0.03
ρ = -0.34
ρ = -0.16
ρ = -0.03
ρ = -0.09
ρ = 0.12
ρ = -0.26
ρ = -0.03
ρ = -0.10
ρ = -0.20
ρ = 0.11
ρ = -0.05
ρ = -0.18
ρ = 0.04
ρ = -0.06
ρ = -0.29
ρ = 0.03
ρ = -0.13
ρ = -0.27
ρ = 0.05
ρ = -0.10
ρ = -0.16
ρ = 0.06
ρ = -0.01
ρ = -0.39
ρ = 0.02
ρ = -0.24
ρ = -0.28
ρ = 0.08
ρ = -0.14
ρ = -0.56
ρ = 0.01
ρ = -0.40

From the above, the largest positive correlations are: 1. Grad Degree - Ex Likely & Primary Election Average Turnout (corr = 0.12) 2. Bach Degree - Ex Likely & Primary Election Average Turnout (corr = 0.11) 3. Bach Degree - Likely & Primary Election Average Turnout (corr = 0.08)

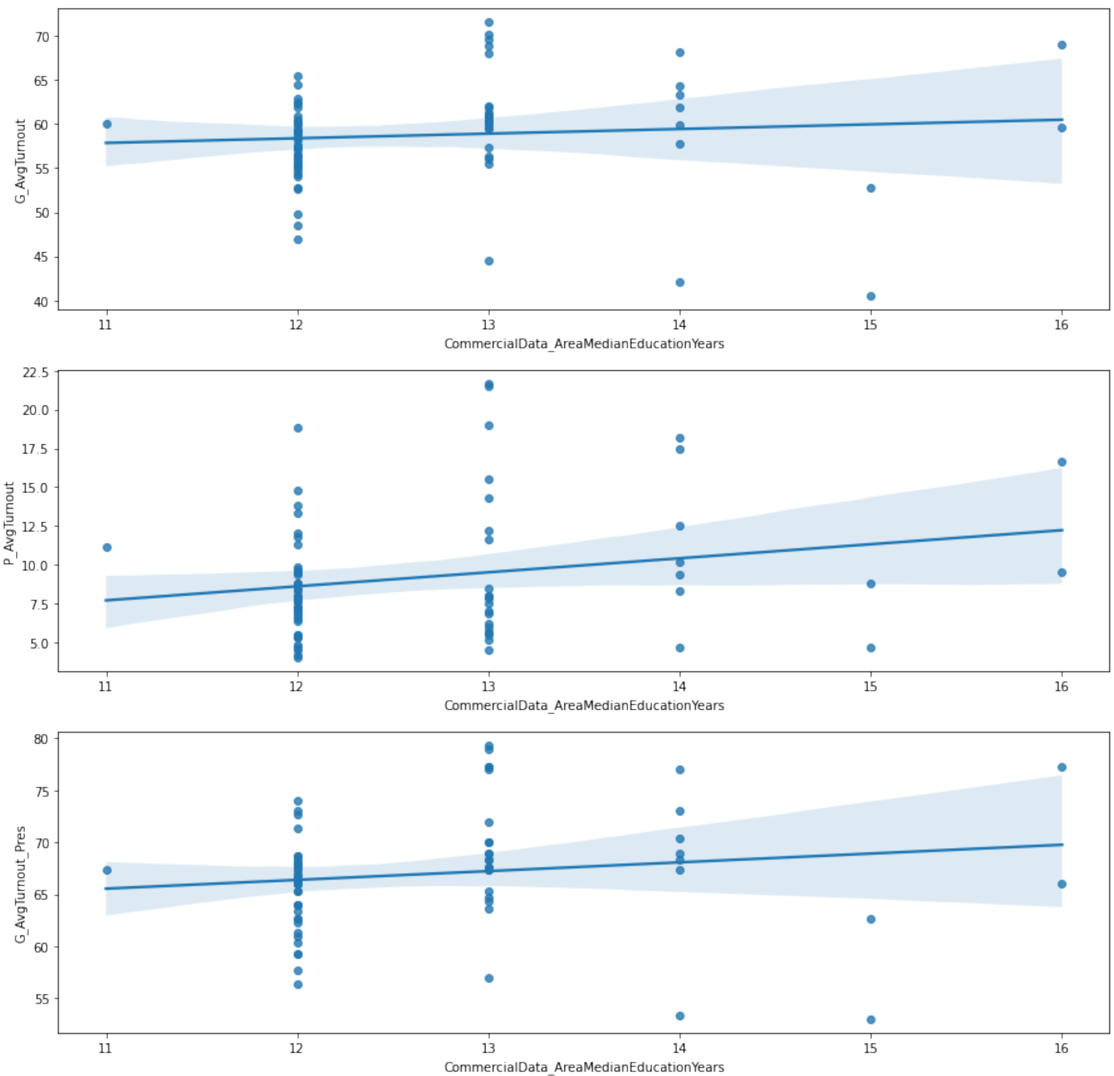
From the above, the largest negative correlations are: 1. Less than HS Diploma - Likely & General Election Average Turnout (corr = -0.56) 2. Less than HS Diploma - Likely & General (2008, 2012, 2016) Election Average Turnout (corr = -0.40) 3. HS Diploma - Likely & General Election Average Turnout (corr = -0.39)

We have some evidence that those with a HS diploma or less are less likely to turnout to General elections, and these negative correlations are decently strong. Furthermore, we don't see evidence of strong correlation for greater education and General election turnout. Rather, the strongest positive correlations for average voter turnout present mixed results with respect to Primary elections across Grad degree and Bach degree education classes, with all weak correlations.

However, a problem with the above is that we are comparing the raw subpopulation numbers for each education class. We could convert these into a percentage to compare against the average percentage of voter turnout, but this raises another issue due to the large number of people with 'Unknown' education level that may also skew the percentages.

Instead of looking at raw education numbers, let's quickly take a look at Median years of education (50th percentile for education years) referenced against average voter turnout.

[30]:
```
fig, (ax1, ax2, ax3) = plt.subplots(ncols=1, nrows=3, figsize=(15, 15))
sns.regplot(x = "CommercialData_AreaMedianEducationYears", y = "G_AvgTurnout",␣
↪data = pandas_county_level_df, ax=ax1)
sns.regplot(x = "CommercialData_AreaMedianEducationYears", y = "P_AvgTurnout",␣
↪data = pandas_county_level_df, ax=ax2)
sns.regplot(x = "CommercialData_AreaMedianEducationYears", y =␣
↪"G_AvgTurnout_Pres", data = pandas_county_level_df, ax=ax3);
```



[31]:
```
county_level_df.stat.corr("CommercialData_AreaMedianEducationYears",␣
 ↪"G_AvgTurnout")
```

[31]: 0.29324448383877644

[32]:
```
county_level_df.stat.corr("CommercialData_AreaMedianEducationYears",␣
 ↪"P_AvgTurnout")
```

[32]: 0.22815881710461705

[33]:
```
county_level_df.stat.corr("CommercialData_AreaMedianEducationYears",␣
↪"G_AvgTurnout_Pres")
```

[33]: 0.19214344590337795

While the correlations imply increase in average voter turnout for increasing median education years, the correlations are not strong. Notably, the correlation between education and voter turnout is strongest across General elections, followed by Primary elections and then Presidential elections. Possibly, constituents with greater education are more likely to follow news, articles, and platforms about candidates in non-Presidential General elections or Primary elections, and not just vote in the Presidential General election cycles.

6.3.1 Associate with Census Educational Attainment columns

So far we've been looking at the 'CommercialData_AreaMedianEducationYears' column from the voter turnout dataset. According to the dicitionary, that column is based on 'modeled and self-reported data'. Let's now take a look at actual educational attainment data from the US Census to see if it gives us a different result.

However, we first need to do some additional processing of the Census educational attainment columns. Many of the columns are stratified across more than just education level, but also conflate classes for race, ethnicity, gender, and age. We can't aggregate those columns that are percentage estimates, so we will aggregate columns that are total population estimates. Specifically, columns that match *S1501_C01* provide total estimates that conflate just education and age, so we can sum up the estimates across the age classes for a given education class to get the estimate controlling for all other factors.

[34]:
```
columns_to_drop = [column for column in county_level_df.columns if "S1501" in␣
↪column if ("C01" not in column) or (column.endswith("M"))]
```

[35]:
```
county_level_df = county_level_df.drop(*columns_to_drop)
```

[36]:
```
county_level_df.toPandas().head()
```

[36]:
```
      County  $150000-174999  $100000-124999  $75000-99999  $125000-149999  \
0    ONTARIO             426            2488          4941            2132
1   CHENANGO              64             405          1271             315
2  HAMPSHIRE            1339            4823          7149            2497
3   HERKIMER             115             590          1764             431
4    CHEMUNG             121            1234          2724             678

   $50000-74999  $175000-199999  $35000-49999  $200000-249999  $25000-34999  \
0          3904             525          1506             557           786
1          3044              67           915              64           431
2          2865             876          1490             844           772
3          3732              82          1280              94           661
```

```
4        3903            158          1414              164          1027

   …  S1501_C01_054E  S1501_C01_059E  S1501_C01_060E  S1501_C01_061E  \
0  …             633           42314           24717           32109
1  …              81           37365           26478           31049
2  …            1821           47370           31676           39742
3  …             139           37743           31745           32203
4  …             255           37963           25051           32007

   S1501_C01_062E  S1501_C01_063E  S1501_C01_064E  G_AvgTurnout  P_AvgTurnout  \
0           37964           53482           68326     61.833333      8.333333
1           36967           44021           58770     56.333333      9.333333
2           39990           50729           67636     68.833333     19.000000
3           37161           46782           60274     56.166667      9.666667
4           34704           50807           65109     57.333333      6.000000

   G_AvgTurnout_Pres
0          70.333333
1          64.000000
2          77.333333
3          64.000000
4          65.333333

[5 rows x 105 columns]
```

[37]:
```
pandas_county_level_df = county_level_df.toPandas()
```

[38]:
```
pandas_county_level_df['census_total_population'] =␣
 ↪pandas_county_level_df["S1501_C01_001E"] +␣
 ↪pandas_county_level_df["S1501_C01_006E"]
pandas_county_level_df['census_perc_less_than_HS'] = 100. *␣
 ↪(pandas_county_level_df["S1501_C01_002E"] +␣
 ↪pandas_county_level_df["S1501_C01_007E"] +␣
 ↪pandas_county_level_df["S1501_C01_008E"] ) /␣
 ↪pandas_county_level_df['census_total_population']
pandas_county_level_df['census_perc_HS_grad'] = 100. *␣
 ↪(pandas_county_level_df["S1501_C01_003E"] +␣
 ↪pandas_county_level_df["S1501_C01_009E"] ) /␣
 ↪pandas_county_level_df['census_total_population']
pandas_county_level_df['census_perc_some_college'] = 100. *␣
 ↪(pandas_county_level_df["S1501_C01_004E"] +␣
 ↪pandas_county_level_df["S1501_C01_010E"] +␣
 ↪pandas_county_level_df["S1501_C01_011E"] ) /␣
 ↪pandas_county_level_df['census_total_population']
```

```
pandas_county_level_df['census_perc_Bachelors'] = 100. *␣
↪(pandas_county_level_df["S1501_C01_005E"] +␣
↪pandas_county_level_df["S1501_C01_012E"] ) /␣
↪pandas_county_level_df['census_total_population']
pandas_county_level_df['census_perc_Grad_Prof'] = 100. *␣
↪(pandas_county_level_df["S1501_C01_013E"] ) /␣
↪pandas_county_level_df['census_total_population']
```

[39]:
```
pandas_county_level_df.head()
```

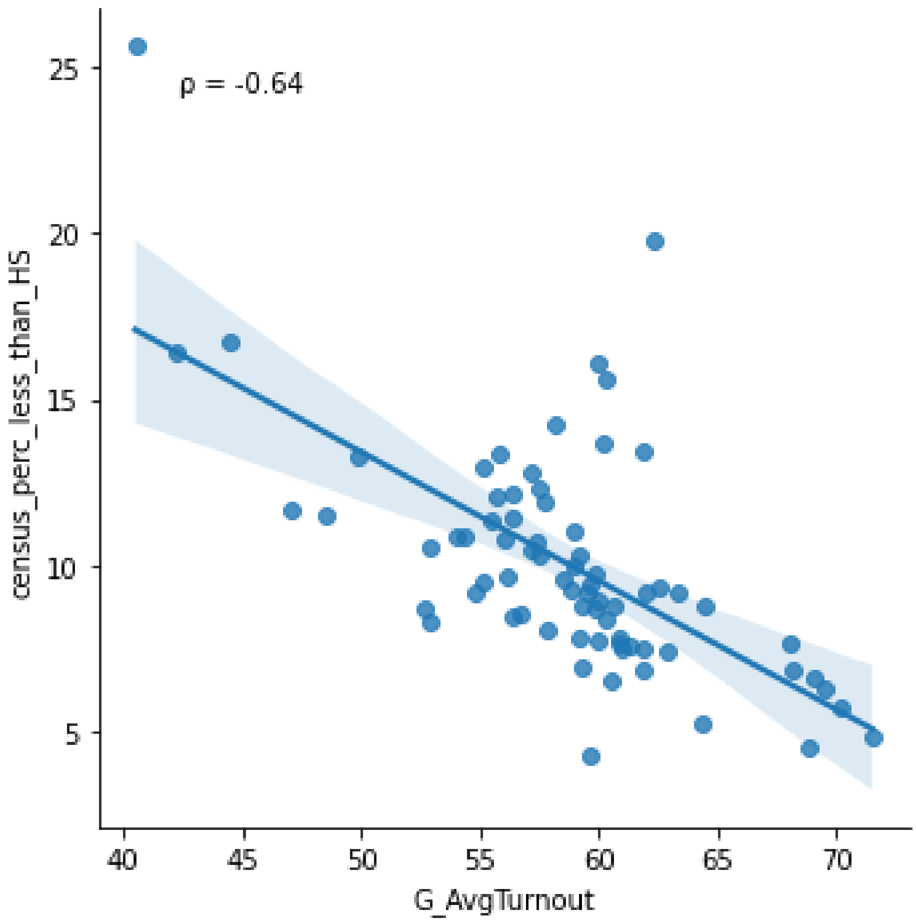
[39]:
```
      County  $150000-174999  $100000-124999  $75000-99999  $125000-149999  \
0    ONTARIO             426            2488          4941            2132
1   CHENANGO              64             405          1271             315
2  HAMPSHIRE            1339            4823          7149            2497
3   HERKIMER             115             590          1764             431
4    CHEMUNG             121            1234          2724             678

   $50000-74999  $175000-199999  $35000-49999  $200000-249999  $25000-34999  \
0          3904             525          1506             557           786
1          3044              67           915              64           431
2          2865             876          1490             844           772
3          3732              82          1280              94           661
4          3903             158          1414             164          1027

   …  S1501_C01_064E  G_AvgTurnout  P_AvgTurnout  G_AvgTurnout_Pres  \
0  …           68326     61.833333      8.333333          70.333333
1  …           58770     56.333333      9.333333          64.000000
2  …           67636     68.833333     19.000000          77.333333
3  …           60274     56.166667      9.666667          64.000000
4  …           65109     57.333333      6.000000          65.333333

   census_total_population  census_perc_less_than_HS  census_perc_HS_grad  \
0                    87686                  6.864266            27.260908
1                    37672                 12.144298            40.475685
2                   137922                  4.574325            19.767695
3                    49028                  9.694460            36.289467
4                    66125                 10.694896            34.791682

   census_perc_some_college  census_perc_Bachelors  census_perc_Grad_Prof
0                 32.647173              18.863901              14.363752
1                 29.494054              10.179975               7.705989
2                 37.959861              19.875727              17.822392
3                 33.931631              12.033940               8.050502
4                 32.541399              12.261626               9.710397

[5 rows x 111 columns]
```

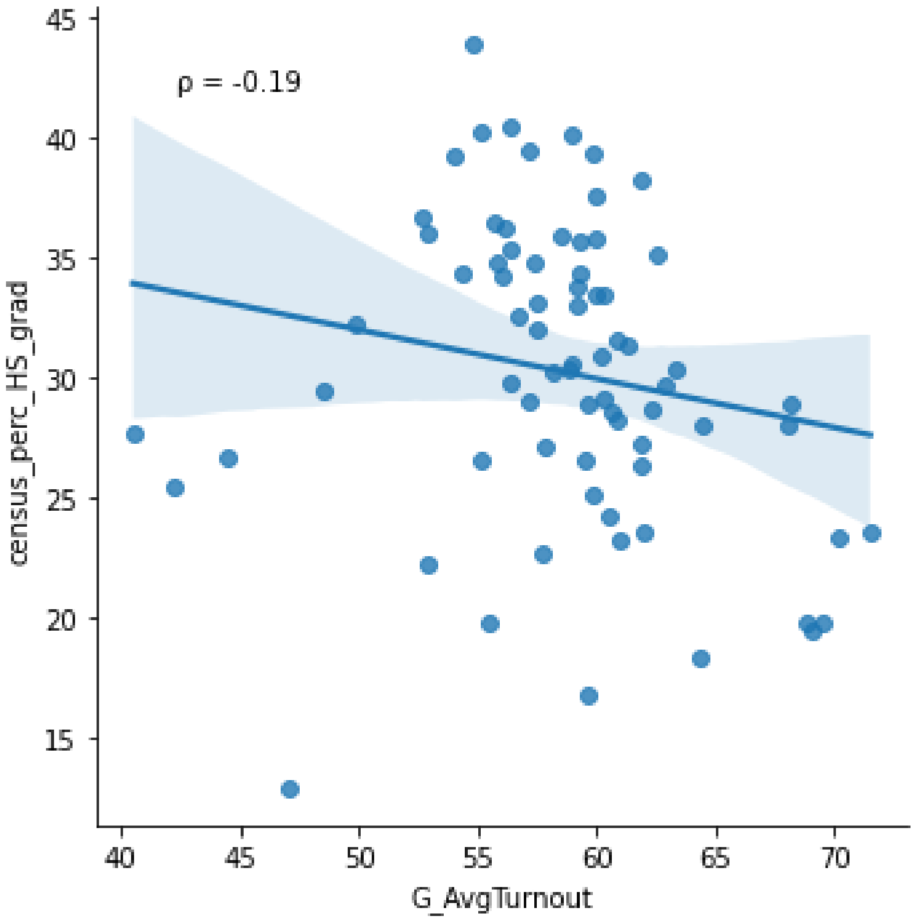
Now let's redo our prior exploratory analysis but with the Census reported educational attainment.

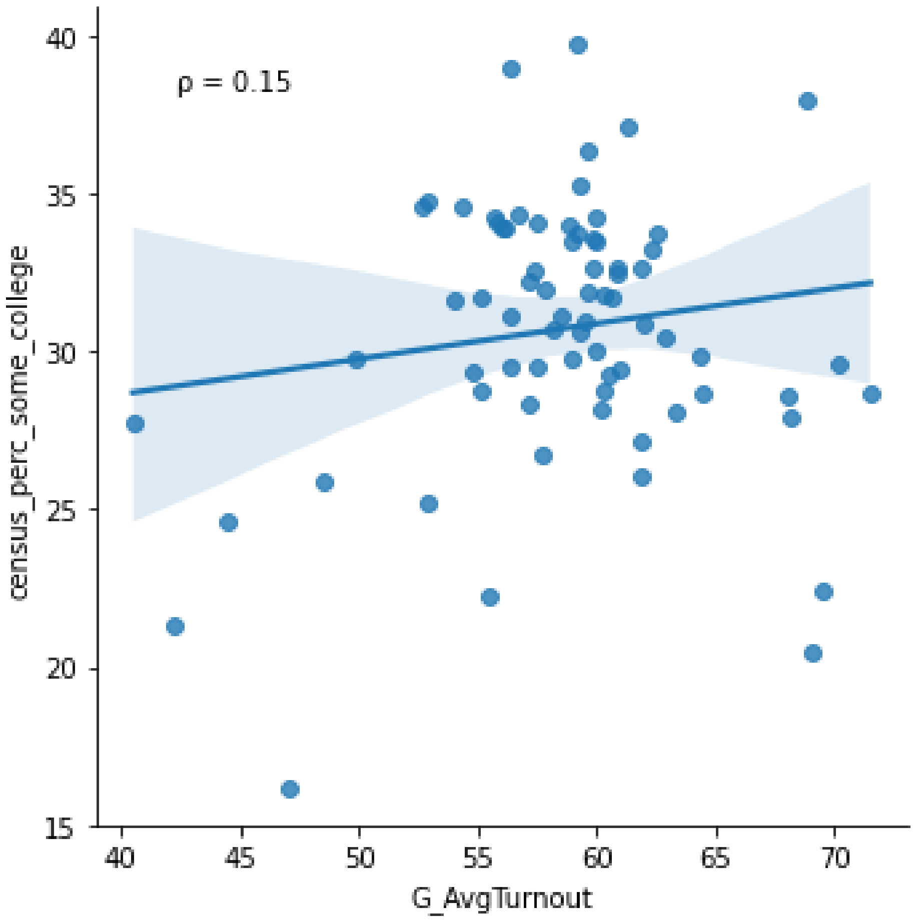
Note that we can't infer causation as we are making the assumption that those who responded in the Census all voted and are the only members of the county that voted.

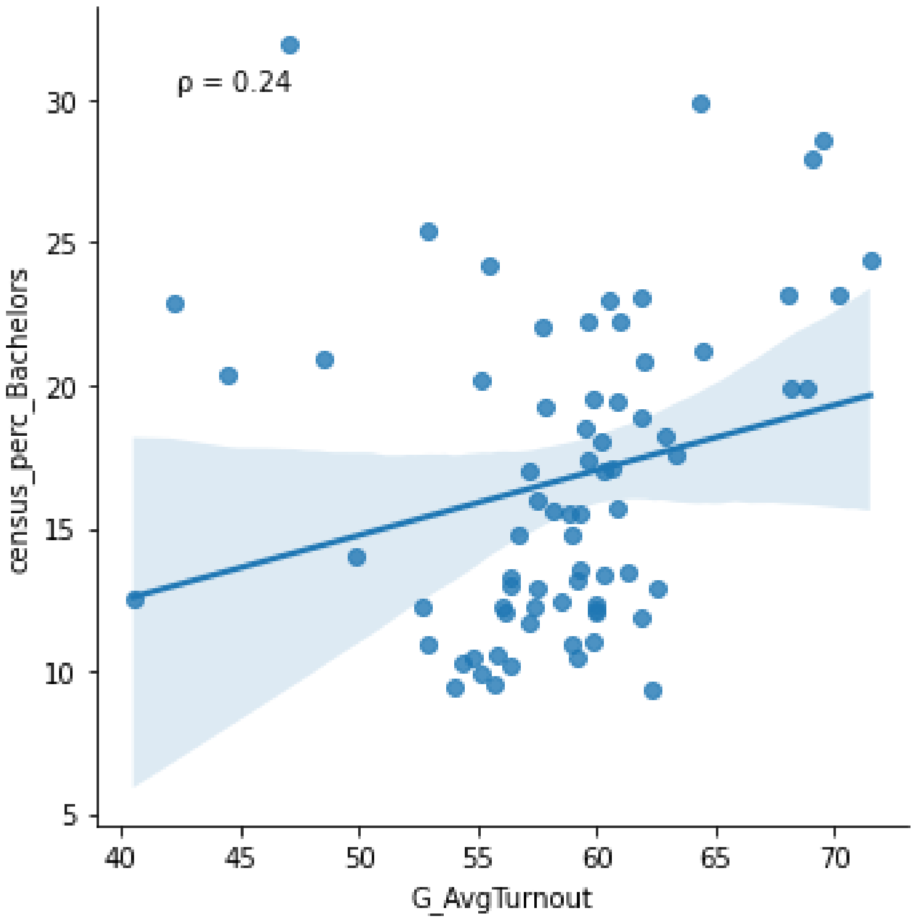
[40]:
```
census_education_level_columns = ['census_perc_less_than_HS',␣
↪'census_perc_HS_grad', 'census_perc_some_college', 'census_perc_Bachelors',␣
↪'census_perc_Grad_Prof']
```

[41]:
```
for _col in ["G_AvgTurnout", "P_AvgTurnout", "G_AvgTurnout_Pres"]:
    for row in census_education_level_columns:
        sns.lmplot(x=_col, y=row, data=pandas_county_level_df)
        corrfunc(pandas_county_level_df[_col], pandas_county_level_df[row])
```

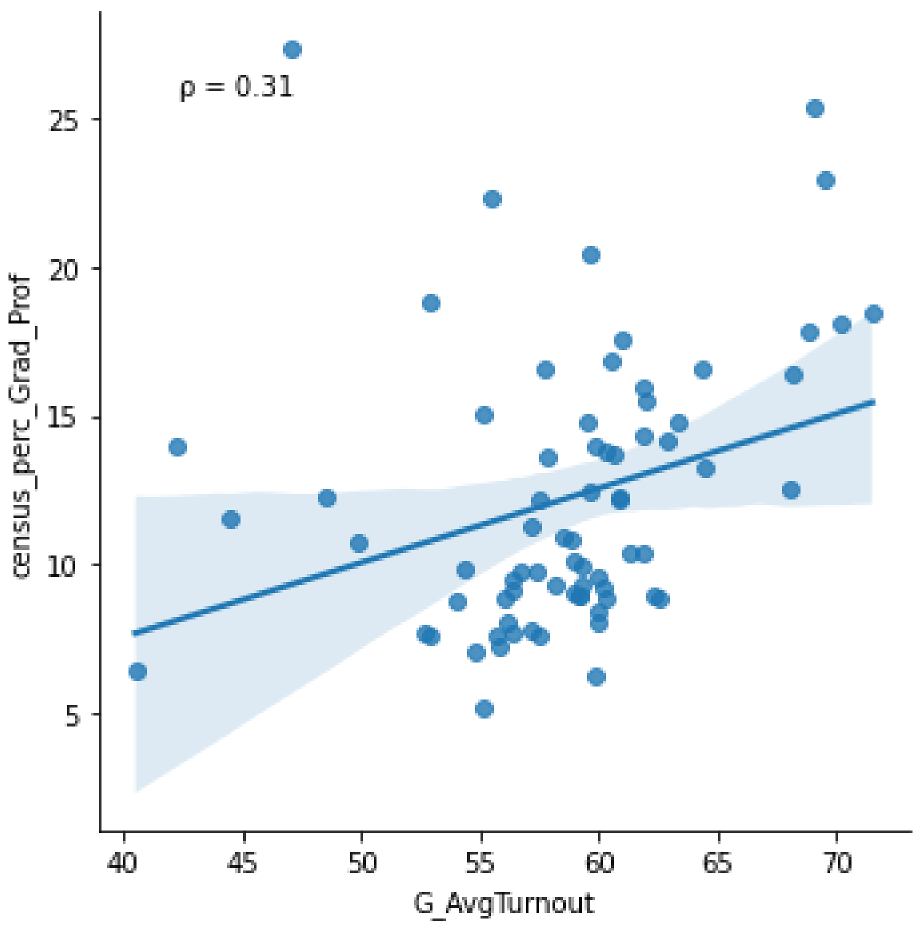


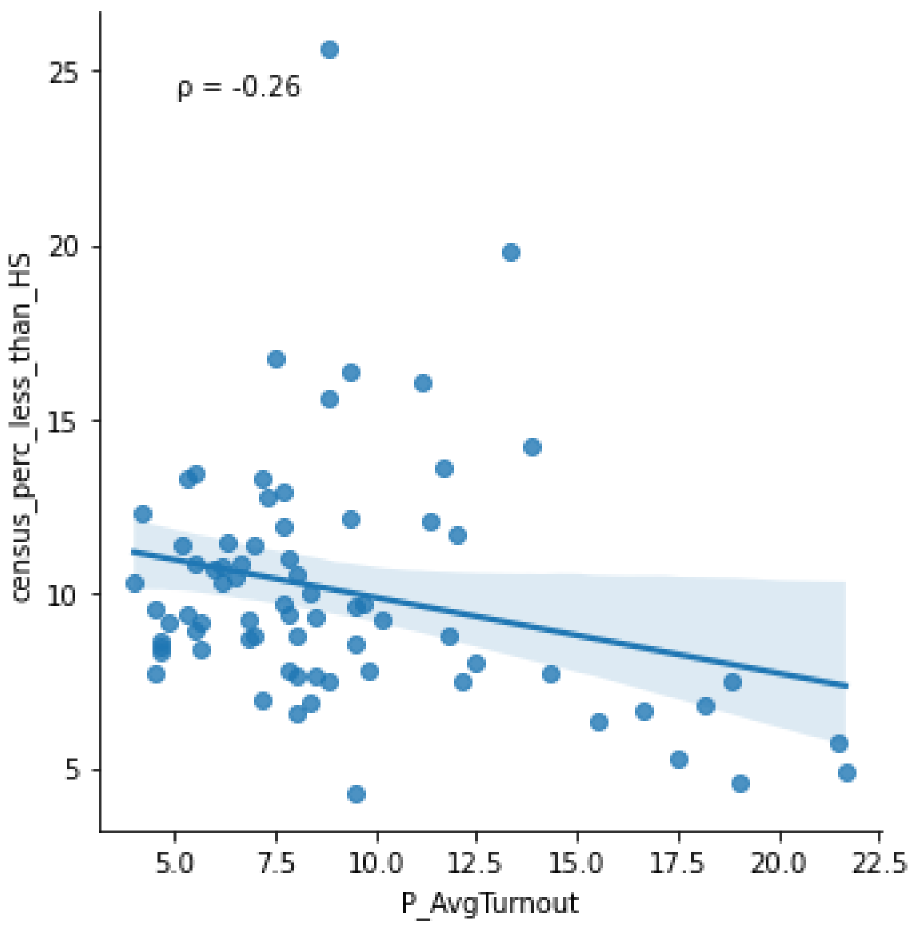

ρ = -0.19
census_perc_HS_grad
G_AvgTurnout
45
40
35
30
25
20
15
40
45
50
55
60
65
70

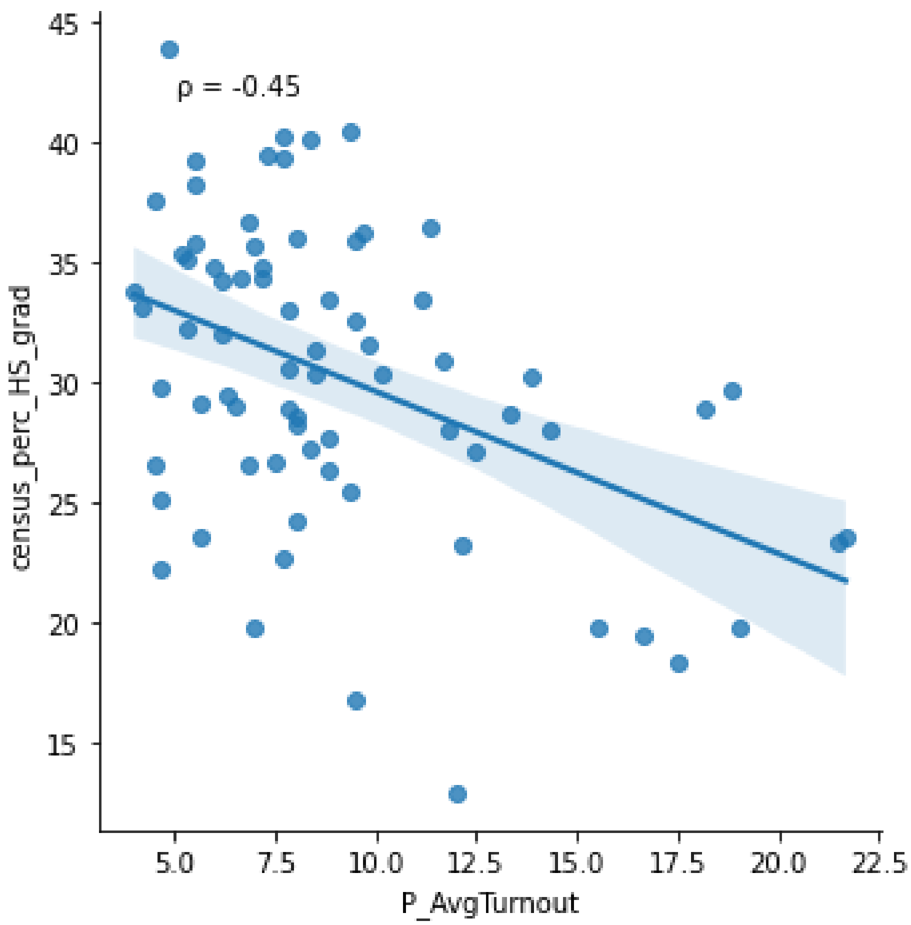

ρ = 0.15
census_perc_some_college
G_AvgTurnout
40
35
30
25
20
15
40
45
50
55
60
65
70



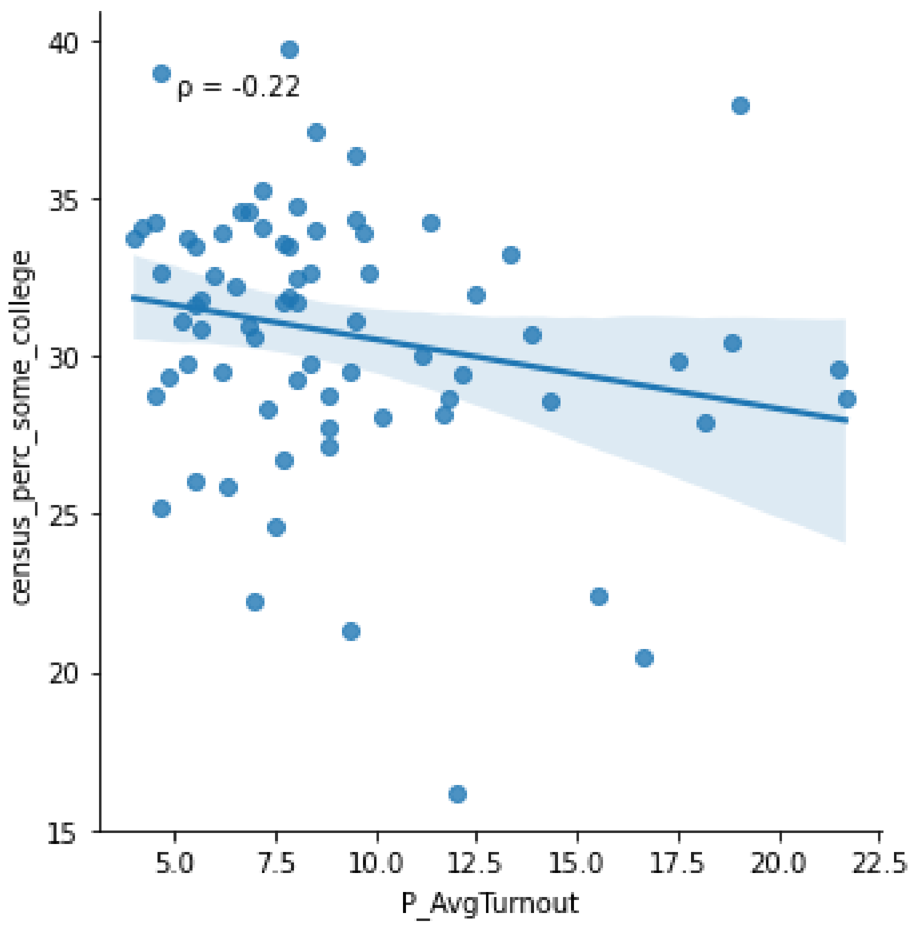
ρ = 0.24
30
25
20
15
10
5
census_perc_Bachelors
40
45
50
55
60
65
70
G_AvgTurnout

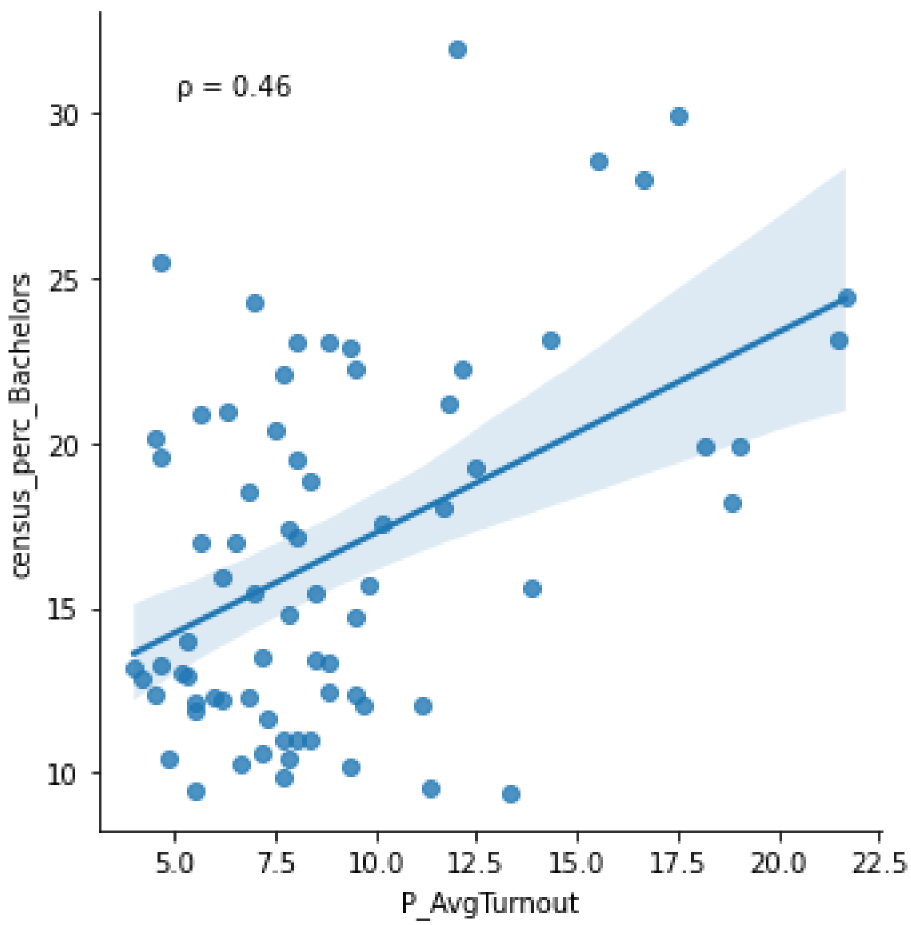

ρ = 0.31
25
20
15
10
5
census_perc_Grad_Prof
40
45
50
55
60
65
70
G_AvgTurnout

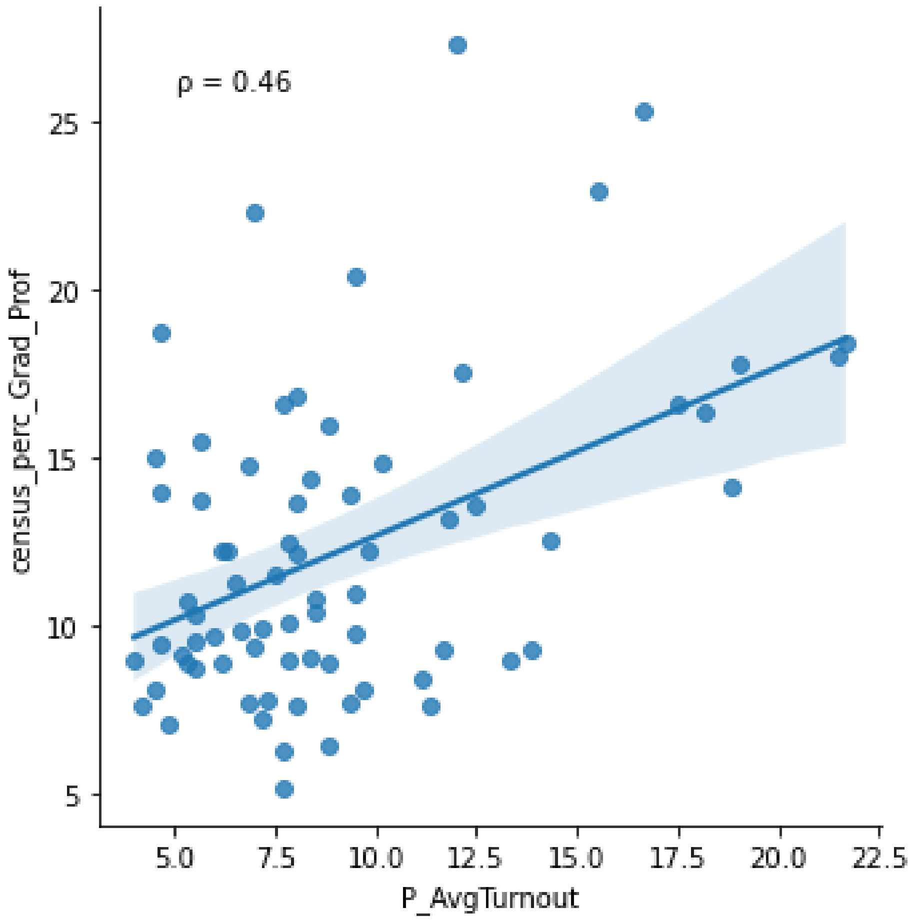

ρ = -0.26
25
20
15
10
5
census_perc_less_than_HS
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
P_AvgTurnout

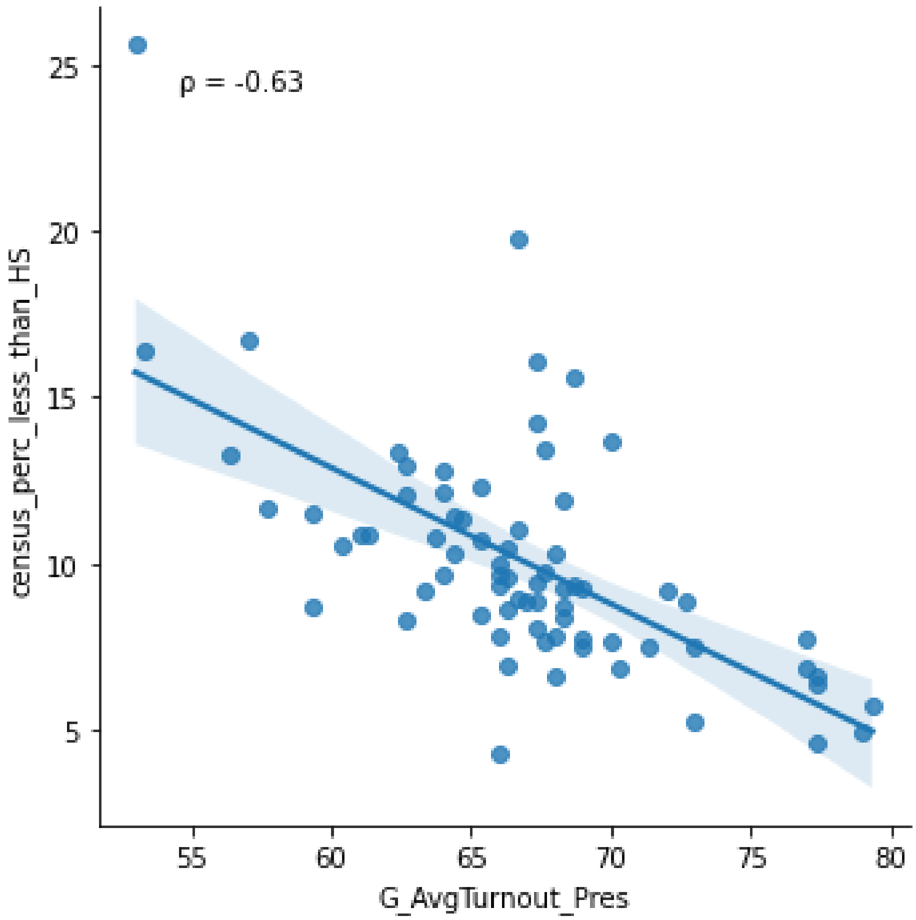


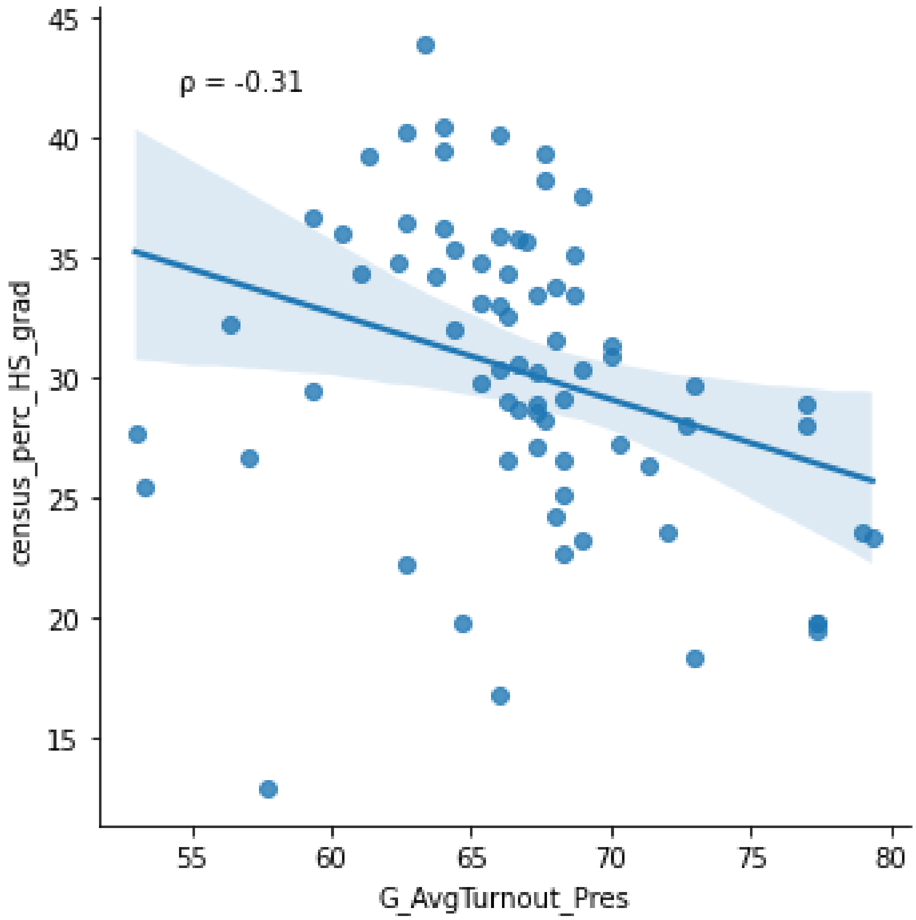
ρ = -0.45
45
40
35
30
25
20
15
census_perc_HS_grad
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
P_AvgTurnout

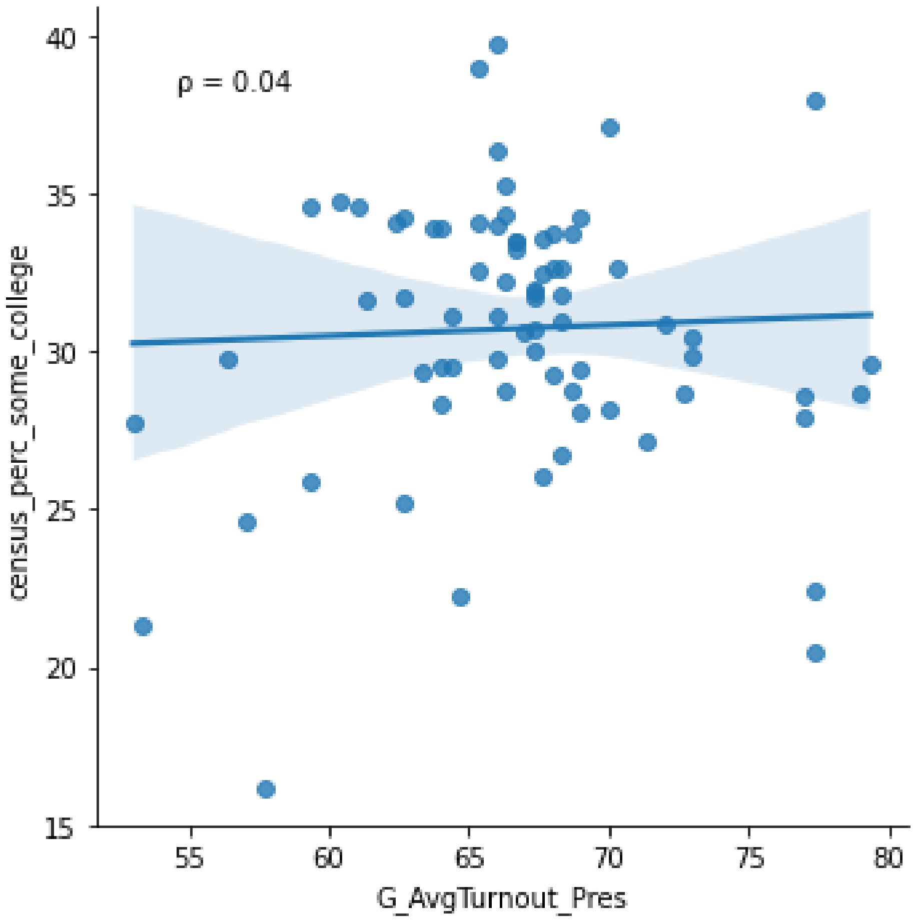

ρ = -0.22
40
35
30
25
20
15
census_perc_some_college
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5
P_AvgTurnout


ρ = 0.46
census_perc_Bachelors
P_AvgTurnout
30
25
20
15
10
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5

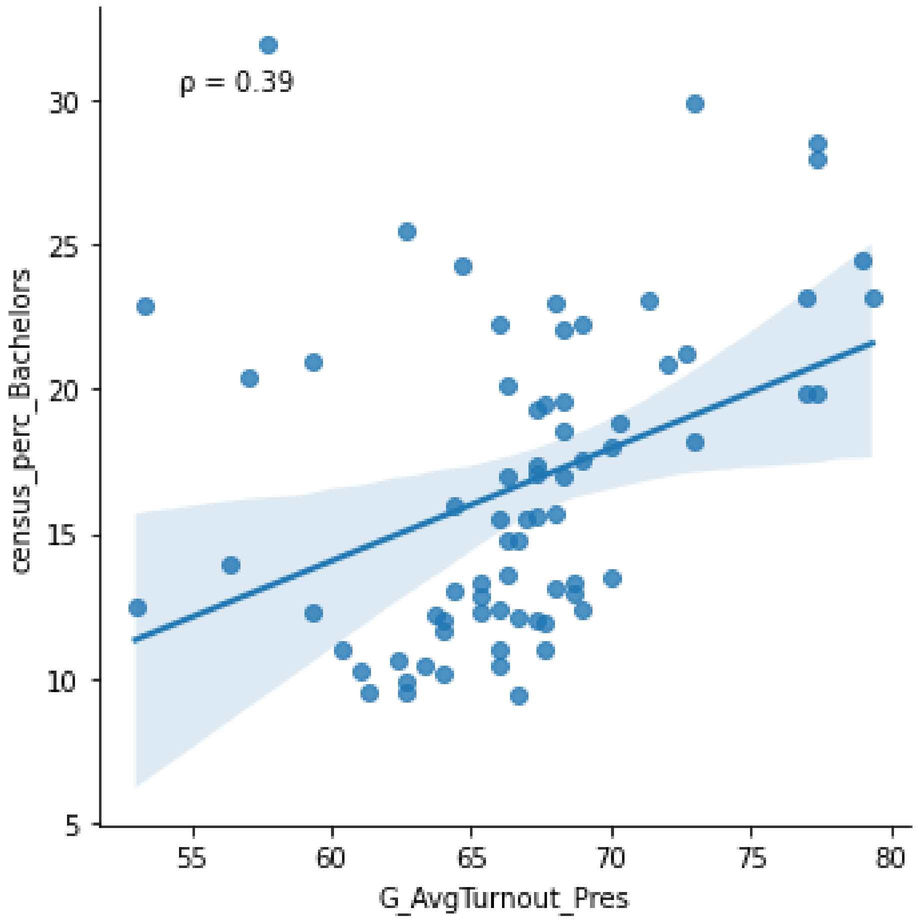

ρ = 0.46
census_perc_Grad_Prof
P_AvgTurnout
5
10
15
20
25
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5

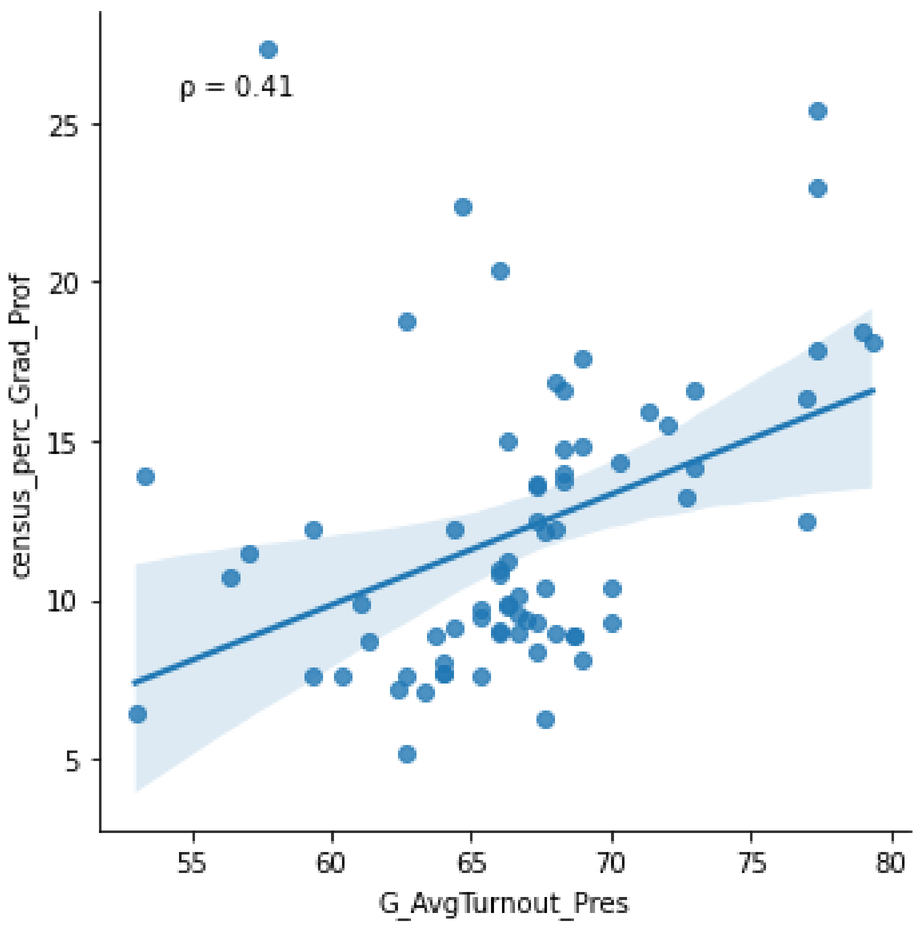

ρ = -0.63
25
20
15
10
5
census_perc_less_than_HS
55
60
65
70
75
80
G_AvgTurnout_Pres


ρ = -0.31
census_perc_HS_grad
G_AvgTurnout_Pres
45
40
35
30
25
20
15
55
60
65
70
75
80



ρ = 0.04
40
35
30
25
20
15
census_perc_some_college
55
60
65
70
75
80
G_AvgTurnout_Pres


ρ = 0.39
census_perc_Bachelors
G_AvgTurnout_Pres
5
10
15
20
25
30
55
60
65
70
75
80



We see much stronger trends from looking at the above plots. Let's visualize all of the correlations for easier examination.

[42]:
```
edu_voter_corr = pandas_county_level_df[['census_perc_less_than_HS',␣
↪'census_perc_HS_grad', 'census_perc_some_college', 'census_perc_Bachelors',␣
↪'census_perc_Grad_Prof', "G_AvgTurnout", "P_AvgTurnout",␣
↪"G_AvgTurnout_Pres"]].corr().drop(columns=census_education_level_columns)
edu_voter_corr = edu_voter_corr.drop(edu_voter_corr.index[[5,6,7]])
```

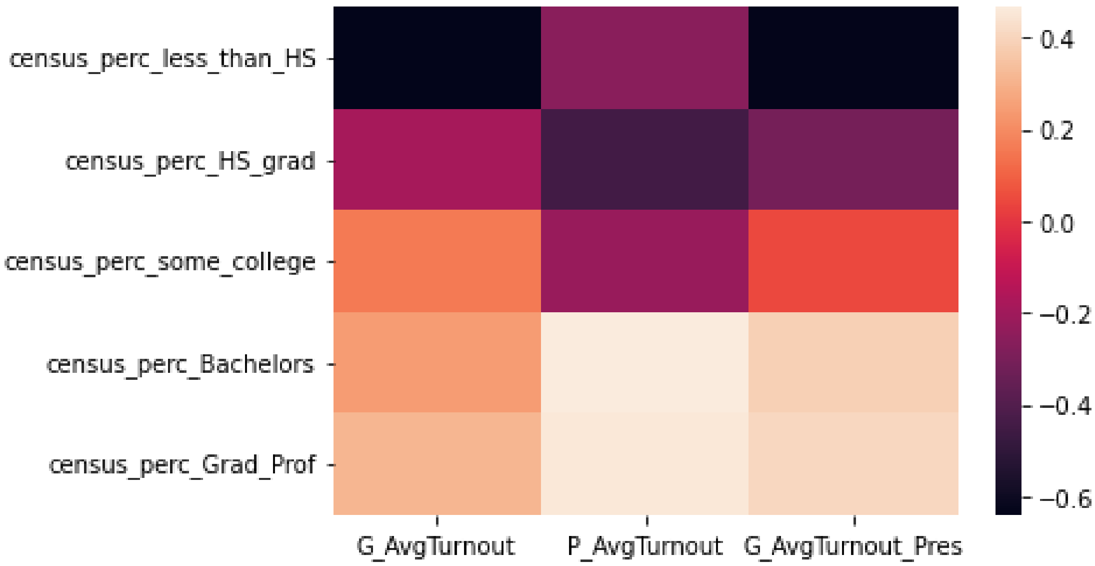
[43]:
```
edu_voter_corr
```

[43]:

	G_AvgTurnout	P_AvgTurnout	G_AvgTurnout_Pres
census_perc_less_than_HS	-0.639701	-0.259159	-0.634127
census_perc_HS_grad	-0.186348	-0.445999	-0.309673
census_perc_some_college	0.154688	-0.218238	0.044270
census_perc_Bachelors	0.241247	0.464806	0.385643
census_perc_Grad_Prof	0.313468	0.455764	0.407787

[44]:
```
sns.heatmap(edu_voter_corr)
```

[44]: <AxesSubplot:>



Education levels of some college or less are mostly associated with 0 or negative correlations. We see strong negative correlations between a county's educational attainment less than HS and its average General election turnouts, regardless of the General election type. There is also a moderate negative correlation for HS grads and Primary election turnout.

Education levels of Bachelors or higher are exclusively associated with positive correlations. We see moderate to strong correlations for Bachelors and Graduate/Professional degree subpopulations and Primary election turnout and General election turnout during Presidential election cycles.

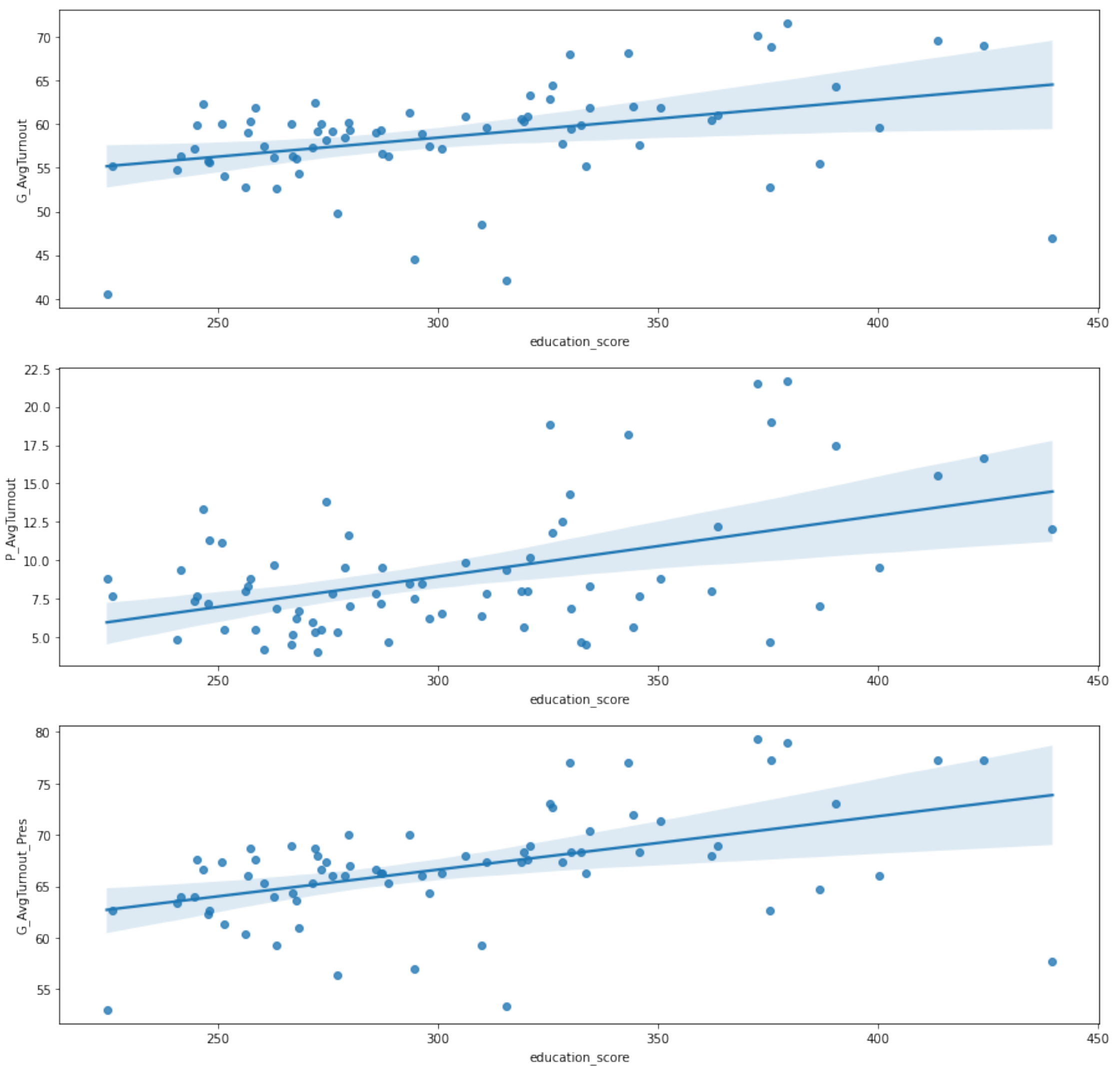
Finally, to define the relationship between the overall education level of a county and its turnouts, we generate the *Education Score* column by:

Education Score = 0 * census_perc_less_than_HS + 1 * census_perc_HS_grad + 3 * census_perc_some_college + 5 * census_perc_Bachelors + 8 * census_perc_Grad_Prof

The coefficients for generating *Education Score* correspond to the number of years of education beyond HS, plus a value of 1 for completing HS. The education attainment data set describes *some college* as typically being an associates degree, so we assign it a value of 2 + 1 = 3. Following, we assume a bachelors takes 2 years beyond an associates degree, and that the professional degrees take an additional 4 years on average to complete (which gives coefficients of 5 and 8, respectively).

[45]:

```
pandas_county_level_df['education_score'] = 0 * pandas_county_level_df['census_perc_less_than_HS'] + 1 * pandas_county_level_df['census_perc_HS_grad'] + 3 * pandas_county_level_df['census_perc_some_college'] + 5 * pandas_county_level_df['census_perc_Bachelors'] + 8 * pandas_county_level_df['census_perc_Grad_Prof']

fig, (ax1, ax2, ax3) = plt.subplots(ncols=1, nrows=3, figsize=(15, 15))
sns.regplot(x = "education_score", y = "G_AvgTurnout", data = pandas_county_level_df, ax=ax1)
sns.regplot(x = "education_score", y = "P_AvgTurnout", data = pandas_county_level_df, ax=ax2)
sns.regplot(x = "education_score", y = "G_AvgTurnout_Pres", data = pandas_county_level_df, ax=ax3);
```



From the above charts, we can conclude that education level has a larger impact on primary elections than on general elections.

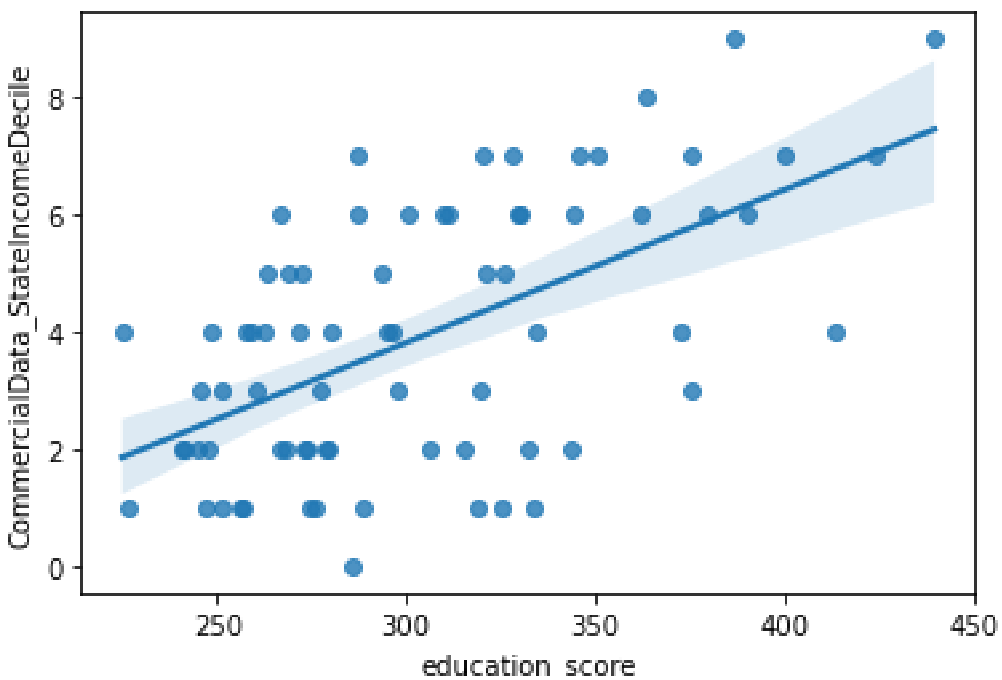
6.3.2 How did education affect election turnouts? By increasing income?

The education level may increase turnouts in a number of ways, such as strengthening people's sense of entitlement, exercising critical thinking, and raising people's income and standard of living to give them a higher willingness to participate in politics. Of these, income is indicator that could be quantified easily. Therefore, we hope to combine education and income to explore the ways in which education affects voting.

First, we need to know whether higher levels of education will lead to higher incomes.

[46]:
```
sns.regplot(x = "education_score", y = "CommercialData_StateIncomeDecile", data␣
↪= pandas_county_level_df)
```

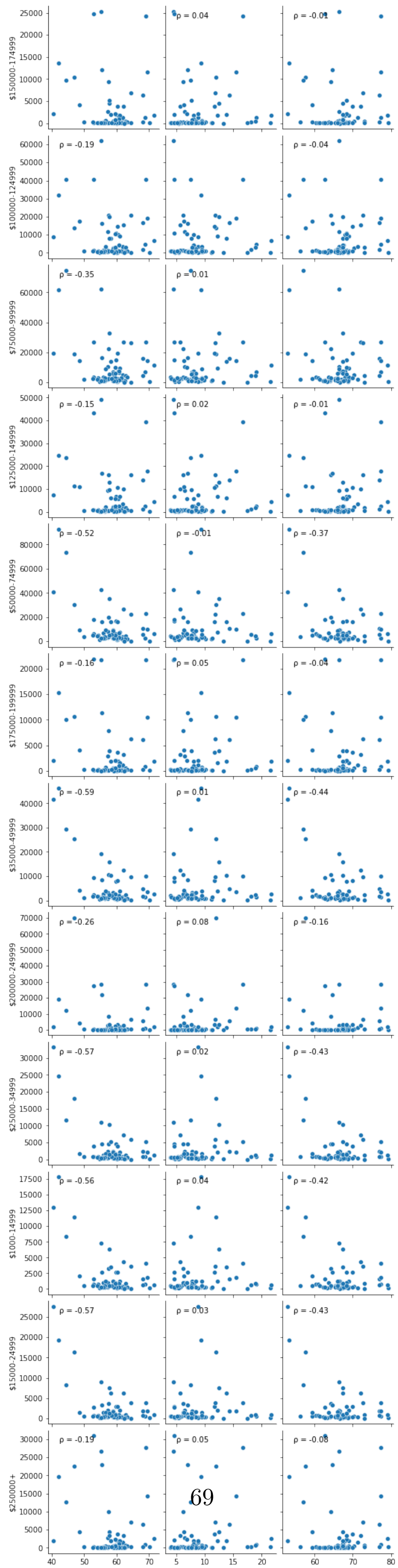
[46]:
```
<AxesSubplot:xlabel='education_score',
ylabel='CommercialData_StateIncomeDecile'>
```



Since we know from the graph that higher education scores have higher income levels, we next need to look at the relationship between income levels and turnout.

[47]:
```
g = sns.pairplot(data=pandas_county_level_df,
             x_vars=['G_AvgTurnout', 'P_AvgTurnout', 'G_AvgTurnout_Pres'],
             y_vars=income_level_columns)
g.map_upper(corrfunc)
```

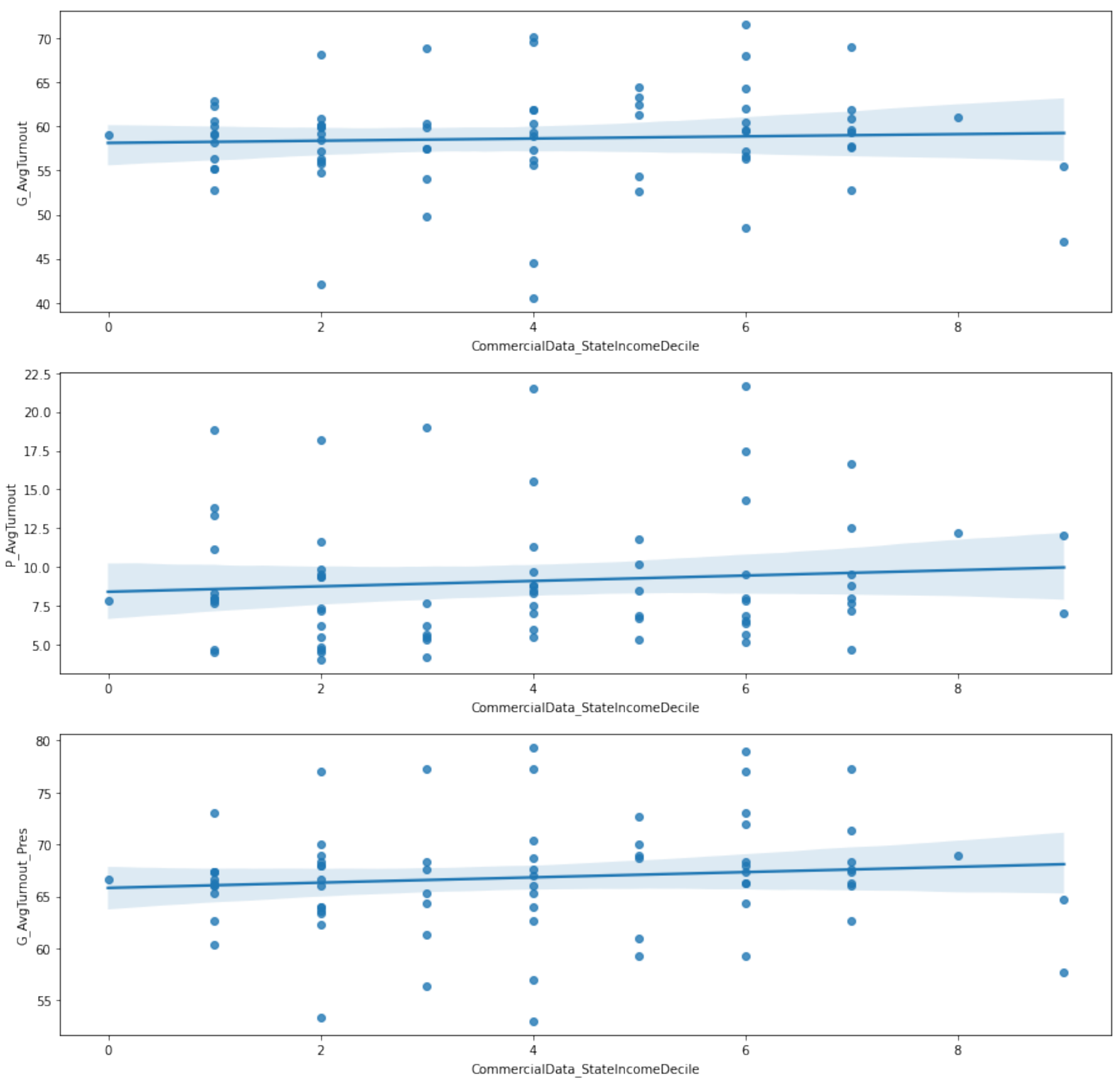
```
g.map_diag(corrfunc)
g.map_lower(corrfunc)
plt.show()
```



$150000-174999
ρ = 0.04
ρ = -0.01
$100000-124999
ρ = -0.19
ρ = -0.04
$75000-99999
ρ = -0.35
ρ = 0.01
$125000-149999
ρ = -0.15
ρ = 0.02
ρ = -0.01
$50000-74999
ρ = -0.52
ρ = -0.01
ρ = -0.37
$175000-199999
ρ = -0.16
ρ = 0.05
ρ = -0.04
$35000-49999
ρ = -0.59
ρ = 0.01
ρ = -0.44
$200000-249999
ρ = -0.26
ρ = 0.08
ρ = -0.16
$25000-34999
ρ = -0.57
ρ = 0.02
ρ = -0.43
$1000-14999
ρ = -0.56
ρ = 0.04
ρ = -0.42
$15000-24999
ρ = -0.57
ρ = 0.03
ρ = -0.43
$250000+
ρ = -0.19
ρ = 0.05
ρ = -0.08
G_AvgTurnout
P_AvgTurnout
G_AvgTurnout_Pres

Although the correlation is small, essentially the number of people in each income tier is inversely correlated with turnout in the general election, positively correlated with turnout in the primary election and hybrid correlated with turnout for presidential candidates.

[48]:
```
fig, (ax1, ax2, ax3) = plt.subplots(ncols=1, nrows=3, figsize=(15, 15))
sns.regplot(x = "CommercialData_StateIncomeDecile", y = "G_AvgTurnout", data =␣
 ↪pandas_county_level_df, ax=ax1)
sns.regplot(x = "CommercialData_StateIncomeDecile", y = "P_AvgTurnout", data =␣
 ↪pandas_county_level_df, ax=ax2)
sns.regplot(x = "CommercialData_StateIncomeDecile", y = "G_AvgTurnout_Pres",␣
 ↪data = pandas_county_level_df, ax=ax3);
```



[49]:
```python
county_level_df.stat.corr("CommercialData_StateIncomeDecile", "G_AvgTurnout")
```

[49]: 0.22600441434634252

[50]:
```python
county_level_df.stat.corr("CommercialData_StateIncomeDecile", "P_AvgTurnout")
```

[50]: 0.0501859484641658

[51]:
```python
county_level_df.stat.corr("CommercialData_StateIncomeDecile",␣
↪"G_AvgTurnout_Pres")
```

[51]: 0.17194980488195782

Next, we looked at the different voter turnout for general, primary and presidential against income decile. The income shares of income deciles show how large share of the total sum of the household income in question each decile gets. The first income decile contains the lowest income tenth and the last one the highest income tenth.

From the three graphs above there is not a clear correlation, whether positive or negative, between the three voter turnout variables and the income decile variable. Furthermore, the correlations are not strong. Notably, the correlation between income decile and voter turnout is strongest across presidential elections. Why would the top decile (wealthier households) tend to vote more for the presidential? Perhaps lower income groups tend to be less politically informed, so they may not give much importance to voting.

[52]:
```python
income_level_columns = ['$150000-174999', '$100000-124999', '$75000-99999',
       '$125000-149999', '$50000-74999', '$175000-199999', '$35000-49999',
       '$200000-249999', '$25000-34999', '$1000-14999', '$15000-24999',
       '$250000+']
```

[53]:
```python
income_voter_corr = pandas_county_level_df[['$150000-174999', '$100000-124999',␣
↪'$75000-99999',
       '$125000-149999', '$50000-74999', '$175000-199999', '$35000-49999',
       '$200000-249999', '$25000-34999', '$1000-14999', '$15000-24999',
       '$250000+', "G_AvgTurnout", "P_AvgTurnout", "G_AvgTurnout_Pres"]].corr().
↪drop(columns=income_level_columns)
income_voter_corr = income_voter_corr.drop(income_voter_corr.index[[12,13,14]])
```

[54]:
```python
income_voter_corr
```

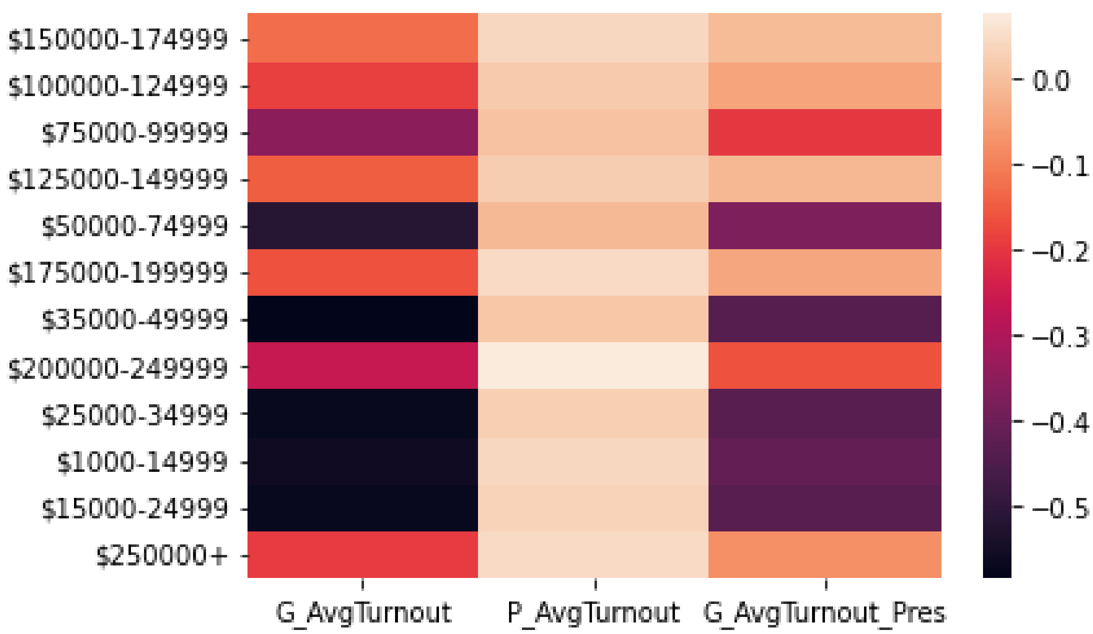
[54]:

	G_AvgTurnout	P_AvgTurnout	G_AvgTurnout_Pres
$150000-174999	-0.127458	0.041136	-0.008602
$100000-124999	-0.190336	0.017686	-0.044548
$75000-99999	-0.353944	0.005167	-0.199055

```
$125000-149999     -0.147048    0.023296        -0.012442
$50000-74999       -0.517647   -0.011492        -0.373951
$175000-199999     -0.164273    0.046950        -0.042087
$35000-49999       -0.585342    0.010920        -0.437853
$200000-249999     -0.260731    0.075382        -0.162586
$25000-34999       -0.571801    0.024366        -0.431291
$1000-14999        -0.558882    0.040292        -0.417465
$15000-24999       -0.570113    0.031949        -0.431773
$250000+           -0.193310    0.046402        -0.078907
```

[55]:
```
sns.heatmap(income_voter_corr)
```

[55]: <AxesSubplot:>

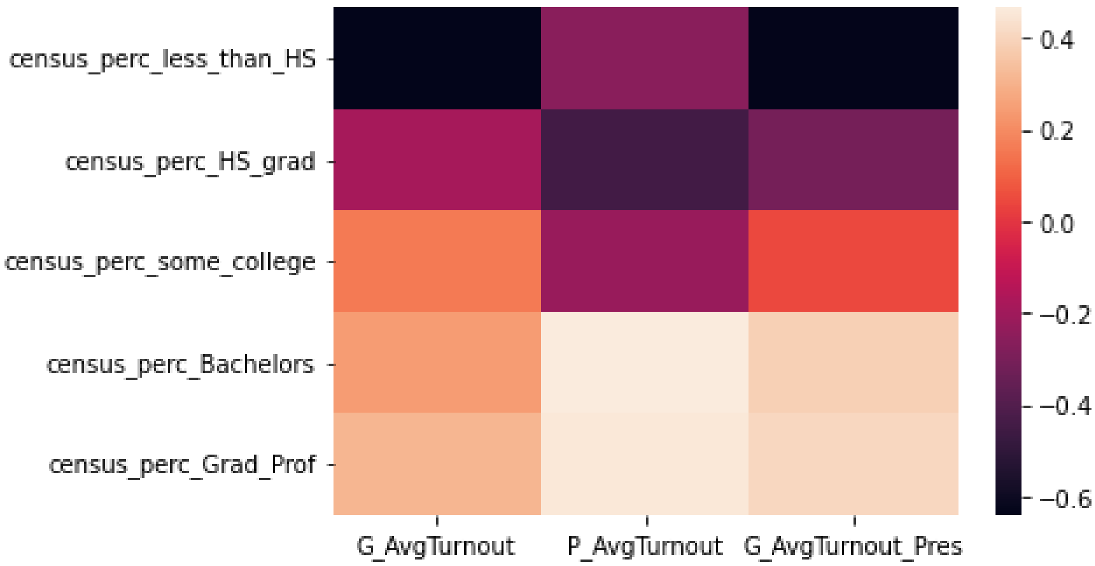


As noted on previous graphs, we do not see strong positive correlations between income and turnout variables. The strongest positive correlation is around 0.08, which is quite low. However, we do see strong negative correlations for the general elections (both presidential and non-presidential). The main takeaway is that even though correlation in general is low, higher income groups tend to have more positive correlation to voter turnout compared to lower income groups. Another surprising finding is that all household income groups had negative correlation with general (presidential and non-presidential) election turnout while all household income groups have positive, albeit weak, correlation with primary election turnout (except for one decile).

For reference, we provide the education level to voter turnout correlation heat map below. We identify some overlap in strong negative correlations for voter turnout between lower income deciles and lower education levels. Thus, income is a potential confounder for education level when attempting to predict its effect on voter turnout.

[56]:
```
# Compare to the education heatmap
sns.heatmap(edu_voter_corr)
```

[56]: <AxesSubplot:>



7 Machine Learning Models

The target of our model is to predict county voter turnout based on features such as education levels of the constituency. Our motivation is that we could then identify the relationship between education and voter turnout, which would help guide policy recommendations on education reform or increasing civic education programs.

Our models are focused on two questions: 1. Which variables have higher importance for a county's voter turnout? 2. Which turnout rate is more suitable for prediction by education level?

We use county_level_df to train our model, which includes average turnouts, percentage of population with different education levels, and number of people in different income brackets.

Because in our previous analysis, we found that income and education have independent effects on turnout, we decided to include income as control variables when assessing the feature importance of education level.

[18]:
```
data = spark.read.parquet("gs://project_bucket_real/notebooks/jupyter/data/
↪modeling.parquet")
```

[19]:
```
data.toPandas().head(5)
```

```
[19]:    G_AvgTurnout  P_AvgTurnout  G_AvgTurnout_Pres  census_perc_less_than_HS  \
      0     57.500000      6.166667          64.333333                 10.320910
      1     58.833333      8.500000          66.000000                  9.307582
      2     60.666667      8.000000          67.333333                  8.823630
      3     60.000000      5.500000          66.666667                  8.968765
      4     61.333333      8.500000          70.000000                  7.614672

         census_perc_HS_grad  census_perc_some_college  census_perc_Bachelors  \
      0            31.979160                 29.556351              15.949626
      1            30.377172                 34.006186              15.489820
      2            28.605286                 31.753080              17.135794
      3            35.840432                 33.527253              12.119953
      4            31.385290                 37.125610              13.453035

         census_perc_Grad_Prof  150000_174999  100000_124999  75000_99999  \
      0              12.193953            192            482          449
      1              10.819240              8             53          132
      2              13.682210             19             91          136
      3               9.543597              1              8           12
      4              10.421393              4             16           49

         125000_149999  50000_74999  175000_199999  35000_49999  200000_249999  \
      0            305          387            164          211            175
      1             39          163             10           62             13
      2             61          138             26           36             13
      3              5           22              1            3              0
      4             19           53              3           27              2

         25000_34999  1000_14999  15000_24999  250000_
      0           96          76           71      178
      1           49          30           38       10
      2           26          18           24       17
      3            6           1            1        1
      4            5          11            9        3
```

7.1 Data processing

Our conty-level voter turnout dataset is not in an appropriate format for input into MLlib's machine learning algorithms. We apply RFormula to transform our dataset into the proper format.

Further, we previously defined three election segments for analysis of voter turnout: 1. The past 6 General elections 2. The past 6 Primary elections 3. The past 3 General elections that include Presidential election (2008, 2012, 2016)

Thus, we create three subsets of our county-level voter turnout dataset. Our naming conventions for the rest of the notebook are described below: 1. Variables appended with `G_avg` match the segment of past 6 general elections 2. Variables appended with `P_avg` match the segment of past 6 primary elections 3. Variables appended with `G_avg_pres` match the segment of past 3 general elections that included Presidential election (2008, 2012, 2016)

[20]:
```
data_G_avg = data.drop("P_AvgTurnout").drop("G_AvgTurnout_Pres")
data_P_avg = data.drop("G_AvgTurnout").drop("G_AvgTurnout_Pres")
data_G_avg_pres = data.drop("P_AvgTurnout").drop( "G_AvgTurnout")

supervised_G_avg = RFormula(formula="G_AvgTurnout ~ .")
supervised_P_avg = RFormula(formula="P_AvgTurnout ~ .")
supervised_G_avg_pres = RFormula(formula="G_AvgTurnout_Pres ~ .")

fittedRF_G_avg = supervised_G_avg.fit(data_G_avg)
fittedRF_P_avg = supervised_P_avg.fit(data_P_avg)
fittedRF_G_avg_pres = supervised_G_avg_pres.fit(data_G_avg_pres)

preparedDF_G_avg = fittedRF_G_avg.transform(data_G_avg)
preparedDF_P_avg = fittedRF_P_avg.transform(data_P_avg)
preparedDF_G_avg_pres = fittedRF_G_avg_pres.transform(data_G_avg_pres)
```

[21]:
```
preparedDF_G_avg.toPandas().head(3)
```

```
22/05/02 00:38:30 WARN org.apache.spark.sql.catalyst.util.package: Truncated the
string representation of a plan since it was too large. This behavior can be
adjusted by setting 'spark.sql.debug.maxToStringFields'.
```

[21]:
```
   G_AvgTurnout  census_perc_less_than_HS  census_perc_HS_grad  \
0     57.500000                 10.320910            31.979160
1     58.833333                  9.307582            30.377172
2     60.666667                  8.823630            28.605286

   census_perc_some_college  census_perc_Bachelors  census_perc_Grad_Prof  \
0                 29.556351              15.949626              12.193953
1                 34.006186              15.489820              10.819240
2                 31.753080              17.135794              13.682210

   150000_174999  100000_124999  75000_99999  125000_149999  50000_74999  \
0            192            482          449            305          387
1              8             53          132             39          163
2             19             91          136             61          138

   175000_199999  35000_49999  200000_249999  25000_34999  1000_14999  \
0            164          211            175           96          76
1             10           62             13           49          30
2             26           36             13           26          18

   15000_24999  250000_                                        features  \
0           71      178  [10.320910311321358, 31.97916000767116, 29.556…
1           38       10  [9.307581539812608, 30.37717208112977, 34.0061…
2           24       17  [8.823629565560875, 28.605286277607895, 31.753…

       label
```

```
0   57.500000
1   58.833333
2   60.666667
```

We standardize the data using StandardScaler, which scales each input feature column according to the range of values in that column to have zero mean and unit variance in each dimension.

[22]:
```
ss = StandardScaler(inputCol="features", outputCol="scaledFeatures")

FittedSs_G_avg = ss.fit(preparedDF_G_avg).transform(preparedDF_G_avg)
FittedSs_P_avg = ss.fit(preparedDF_P_avg).transform(preparedDF_P_avg)
FittedSs_G_avg_pres = ss.fit(preparedDF_G_avg_pres).
 ↪transform(preparedDF_G_avg_pres)
```

If we examine the processed data, we see that the scaledFeatures column was correctly output to each dataset.

[23]:
```
FittedSs_G_avg.toPandas().head()
```

[23]:
```
   G_AvgTurnout  census_perc_less_than_HS  census_perc_HS_grad  \
0     57.500000                 10.320910            31.979160
1     58.833333                  9.307582            30.377172
2     60.666667                  8.823630            28.605286
3     60.000000                  8.968765            35.840432
4     61.333333                  7.614672            31.385290

   census_perc_some_college  census_perc_Bachelors  census_perc_Grad_Prof  \
0                 29.556351              15.949626              12.193953
1                 34.006186              15.489820              10.819240
2                 31.753080              17.135794              13.682210
3                 33.527253              12.119953               9.543597
4                 37.125610              13.453035              10.421393

   150000_174999  100000_124999  75000_99999  125000_149999  …  \
0            192            482          449            305  …
1              8             53          132             39  …
2             19             91          136             61  …
3              1              8           12              5  …
4              4             16           49             19  …

   175000_199999  35000_49999  200000_249999  25000_34999  1000_14999  \
0            164          211            175           96          76
1             10           62             13           49          30
2             26           36             13           26          18
3              1            3              0            6           1
4              3           27              2            5          11
```

```
   15000_24999  250000_                                          features  \
0           71      178  [10.320910311321358, 31.97916000767116, 29.556…
1           38       10  [9.307581539812608, 30.37717208112977, 34.0061…
2           24       17  [8.823629565560875, 28.605286277607895, 31.753…
3            1        1  [8.968765149941131, 35.840432162892164, 33.527…
4            9        3  [7.614671844361567, 31.385289707408973, 37.125…

       label                                     scaledFeatures
0  57.500000  [2.957077072339297, 5.060968450532359, 7.05079…
1  58.833333  [2.6667450002077024, 4.80744051695265, 8.11232…
2  60.666667  [2.528086369911949, 4.527024829129103, 7.57483…
3  60.000000  [2.569669631078422, 5.672046932637733, 7.99807…
4  61.333333  [2.181704020782869, 4.9669835287078286, 8.8564…

[5 rows x 21 columns]
```

[24]:

```python
FittedSs_P_avg.toPandas().head()
```

[24]:

```
   P_AvgTurnout  census_perc_less_than_HS  census_perc_HS_grad  \
0      6.166667                 10.320910            31.979160
1      8.500000                  9.307582            30.377172
2      8.000000                  8.823630            28.605286
3      5.500000                  8.968765            35.840432
4      8.500000                  7.614672            31.385290

   census_perc_some_college  census_perc_Bachelors  census_perc_Grad_Prof  \
0                 29.556351              15.949626              12.193953
1                 34.006186              15.489820              10.819240
2                 31.753080              17.135794              13.682210
3                 33.527253              12.119953               9.543597
4                 37.125610              13.453035              10.421393

   150000_174999  100000_124999  75000_99999  125000_149999  …  \
0            192            482          449            305  …
1              8             53          132             39  …
2             19             91          136             61  …
3              1              8           12              5  …
4              4             16           49             19  …

   175000_199999  35000_49999  200000_249999  25000_34999  1000_14999  \
0            164          211            175           96          76
1             10           62             13           49          30
2             26           36             13           26          18
3              1            3              0            6           1
4              3           27              2            5          11

   15000_24999  250000_                                          features  \
```

```
0           71      178  [10.320910311321358, 31.97916000767116, 29.556…
1           38       10  [9.307581539812608, 30.37717208112977, 34.0061…
2           24       17  [8.823629565560875, 28.605286277607895, 31.753…
3            1        1  [8.968765149941131, 35.840432162892164, 33.527…
4            9        3  [7.614671844361567, 31.385289707408973, 37.125…

      label                                    scaledFeatures
0  6.166667  [2.957077072339297, 5.060968450532359, 7.05079…
1  8.500000  [2.6667450002077024, 4.80744051695265, 8.11232…
2  8.000000  [2.528086369911949, 4.527024829129103, 7.57483…
3  5.500000  [2.569669631078422, 5.672046932637733, 7.99807…
4  8.500000  [2.181704020782869, 4.9669835287078286, 8.8564…

[5 rows x 21 columns]
```

[25]:
```python
FittedSs_G_avg_pres.toPandas().head()
```

[25]:
```
   G_AvgTurnout_Pres  census_perc_less_than_HS  census_perc_HS_grad  \
0          64.333333                 10.320910            31.979160
1          66.000000                  9.307582            30.377172
2          67.333333                  8.823630            28.605286
3          66.666667                  8.968765            35.840432
4          70.000000                  7.614672            31.385290

   census_perc_some_college  census_perc_Bachelors  census_perc_Grad_Prof  \
0                 29.556351              15.949626              12.193953
1                 34.006186              15.489820              10.819240
2                 31.753080              17.135794              13.682210
3                 33.527253              12.119953               9.543597
4                 37.125610              13.453035              10.421393

   150000_174999  100000_124999  75000_99999  125000_149999  …  \
0            192            482          449            305  …
1              8             53          132             39  …
2             19             91          136             61  …
3              1              8           12              5  …
4              4             16           49             19  …

   175000_199999  35000_49999  200000_249999  25000_34999  1000_14999  \
0            164          211            175           96          76
1             10           62             13           49          30
2             26           36             13           26          18
3              1            3              0            6           1
4              3           27              2            5          11

   15000_24999  250000_                                         features  \
0           71      178  [10.320910311321358, 31.97916000767116, 29.556…
```

```
1          38       10  [9.307581539812608, 30.37717208112977, 34.0061…
2          24       17  [8.823629565560875, 28.605286277607895, 31.753…
3           1        1  [8.968765149941131, 35.840432162892164, 33.527…
4           9        3  [7.614671844361567, 31.385289707408973, 37.125…

       label                                     scaledFeatures
0  64.333333  [2.957077072339297, 5.060968450532359, 7.05079…
1  66.000000  [2.6667450002077024, 4.80744051695265, 8.11232…
2  67.333333  [2.528086369911949, 4.527024829129103, 7.57483…
3  66.666667  [2.569669631078422, 5.672046932637733, 7.99807…
4  70.000000  [2.181704020782869, 4.9669835287078286, 8.8564…

[5 rows x 21 columns]
```

We now randomly split each dataset into separate train and test splits, using a 70/30 train/test ratio.

[26]:
```
train_G_avg, test_G_avg = FittedSs_G_avg.randomSplit(weights=[0.7,0.3],␣
↪seed=843)
train_P_avg, test_P_avg = FittedSs_P_avg.randomSplit(weights=[0.7,0.3],␣
↪seed=843)
train_G_avg_pres, test_G_avg_pres = FittedSs_G_avg_pres.randomSplit(weights=[0.
↪7,0.3], seed=843)
```

We retrieve the name of the columns used to construct a feature vector stored in a Pandas DataFrame. This will be useful for later.

[27]:
```
featureCols = pd.DataFrame(preparedDF_G_avg.drop('G_AvgTurnout').
↪drop('features').drop('label').columns, columns = ['name'])
featureCols
```

[27]:
```
                       name
0    census_perc_less_than_HS
1          census_perc_HS_grad
2    census_perc_some_college
3        census_perc_Bachelors
4        census_perc_Grad_Prof
5                150000_174999
6                100000_124999
7                  75000_99999
8                125000_149999
9                  50000_74999
10               175000_199999
11                 35000_49999
12               200000_249999
13                 25000_34999
14                  1000_14999
15                 15000_24999
```

```
16                    250000_
```

We also create a list of those features that are specific to education level, as these will be used later on when assessing importance of education level features.

[28]:
```
educationCol =␣
↪['census_perc_less_than_HS','census_perc_HS_grad','census_perc_some_college','census_perc_B
```

7.2 Modeling

For modeling, we tried ridge regression, decision tree, and random forest. As this is a regression task, we use RMSE as the evaluator.

7.2.1 Model for G_avgturnout

We first try modeling average voter turnout across the past 6 general election cycles.

Ridge regression We instantiate instances for our model (`LinearRegression`) and our evaluator (`RegressionEvaluator`).

[29]:
```
lr = LinearRegression(featuresCol = 'scaledFeatures', elasticNetParam = 0)
```

[30]:
```
evaluator = RegressionEvaluator()
```

We won't train one `LinearRegression` model. Instead, we will train several variations specifying different values for the `regParam` hyperparameter. We hold `elasticNetParam` constant at 0, which entails an L2 penalty that defines our model as ridge regression. For validation and selection of the best model, we use `TrainValidationSplit` with a train ratio of 80%.

[31]:
```
paramsGrid_lr = ParamGridBuilder()\
  .addGrid(lr.regParam, [0.0, 0.05, 0.25, 0.5, 0.75, 1.0])\
  .build()

tvs_lr = TrainValidationSplit(estimator=lr,
                              estimatorParamMaps=paramsGrid_lr,
                              evaluator=evaluator,
                              parallelism=2, seed=843).setTrainRatio(0.8)
```

[32]:
```
tvsFitted_lr_G_avg = tvs_lr.fit(train_G_avg)
```

```
22/05/02 00:38:47 WARN org.apache.spark.ml.util.Instrumentation: [83ebd262]
regParam is zero, which might cause numerical instability and overfitting.
22/05/02 00:38:49 WARN com.github.fommil.netlib.BLAS: Failed to load
implementation from: com.github.fommil.netlib.NativeSystemBLAS
22/05/02 00:38:49 WARN com.github.fommil.netlib.BLAS: Failed to load
implementation from: com.github.fommil.netlib.NativeRefBLAS
22/05/02 00:38:49 WARN com.github.fommil.netlib.LAPACK: Failed to load
implementation from: com.github.fommil.netlib.NativeSystemLAPACK
22/05/02 00:38:49 WARN com.github.fommil.netlib.LAPACK: Failed to load
implementation from: com.github.fommil.netlib.NativeRefLAPACK
```

```
22/05/02 00:38:53 WARN org.apache.spark.ml.util.Instrumentation: [ee7cafa9]
regParam is zero, which might cause numerical instability and overfitting.
22/05/02 00:38:54 WARN org.apache.spark.ml.util.Instrumentation: [ee7cafa9]
Cholesky solver failed due to singular covariance matrix. Retrying with Quasi-
Newton solver.
```

Now let's extract the best performing model and see how well it does on the train and test data sets.

[33]:
```
bestlr_G_avg = tvsFitted_lr_G_avg.bestModel
```

On the training dataset, our RMSE is about 2.32% for average voter turnout. As expected, the test dataset RMSE is higher – around 8.25%

[34]:
```
rmse_lr_G_avg_train = evaluator.evaluate(bestlr_G_avg.transform(train_G_avg),␣
 ↪{evaluator.metricName: "rmse"})
rmse_lr_G_avg_test = evaluator.evaluate(bestlr_G_avg.transform(test_G_avg),␣
 ↪{evaluator.metricName: "rmse"})
print("RMSE for train dataset", rmse_lr_G_avg_train)
print("RMSE for test dataset", rmse_lr_G_avg_test)
```

```
[Stage 36:==============================>                          (1 + 1) / 2]

RMSE for train dataset 2.32310796539245
RMSE for test dataset 8.254549250171191
```

Decision tree We instantiate instances for our model (`DecisionTreeRegressor`). Like with the ridge regression model, we will conduct a hyperparameter search to find and extract the best hyperparameter combination. We will then take the best model and evaluate it in terms of RMSE.

In the case of the Decision Tree, we will search over:
1. `maxDepth`: Maximum depth of a tree. Higher `maxDepth` entails greater expressivity, but also greater computational cost and chance of overfitting.
2. `maxBins`: Number of bins used when discretizing continuous features. Higher `maxBins` entails finer-grained split decisions, but also greater computational cost.

[35]:
```
tree = DecisionTreeRegressor(featuresCol = 'scaledFeatures', seed = 843)
```

[36]:
```
paramsGrid_tree = ParamGridBuilder()\
  .addGrid(tree.maxDepth, [5,15,25])\
  .addGrid(tree.maxBins, [20,30,40])\
  .build()

tvs_tree = TrainValidationSplit(estimator=tree,
                           estimatorParamMaps=paramsGrid_tree,
                           evaluator=evaluator,
                           parallelism=2, seed=843).setTrainRatio(0.8)
```

```
[37]: tvsFitted_tree_G_avg = tvs_tree.fit(train_G_avg)
```

```
[38]: besttree_G_avg = tvsFitted_tree_G_avg.bestModel
```

```
[39]: rmse_tree_G_avg_train = evaluator.evaluate(besttree_G_avg.
       ↪transform(train_G_avg), {evaluator.metricName: "rmse"})
      rmse_tree_G_avg_test = evaluator.evaluate(besttree_G_avg.transform(test_G_avg),␣
       ↪{evaluator.metricName: "rmse"})
      print("RMSE for train dataset", rmse_tree_G_avg_train)
      print("RMSE for test dataset", rmse_tree_G_avg_test)
```

```
RMSE for train dataset 1.828807846475349
RMSE for test dataset 5.826257081066647
```

It looks like the Decision Tree performs better than the Ridge Regressor. Note that we shouldn't base this decision on test dataset performance, as this is not good practice and such human intervention can lead to overfitting. The train dataset RMSE and test dataset RMSE are 1.83% and 5.83%, respectively. These are both better than the Ridge Regressor's performance.

Random forest We instantiate instances for our model (`RandomForestRegressor`). We again conduct a hyperparameter search to find and extract the best hyperparameter combination. We will then take the best model and evaluate it in terms of RMSE.

In the case of the Random Forest, we will search over:
1. `maxDepth`: Maximum depth of each tree. Higher `maxDepth` entails greater expressivity, but also greater computational cost and chance of overfitting.
2. `maxBins`: Number of bins used when discretizing continuous features. Higher `maxBins` entails finer-grained split decisions, but also greater computational cost.
3. `numTrees`: Number of trees in the random forest.
4. `featureSubsetStrategy`: Number of features to consider for splits at each node. Since `numTrees` is always greater than 1, we don't include `auto` as an option in the search since `auto` will be set to `sqrt` if `numTrees` > 1.

```
[40]: rf = RandomForestRegressor(featuresCol = 'scaledFeatures', seed = 843)
```

```
[41]: paramsGrid_rf = ParamGridBuilder()\
        .addGrid(rf.maxDepth, [5,10])\
        .addGrid(rf.maxBins, [20,30,40])\
        .addGrid(rf.numTrees, [20,30])\
        .addGrid(rf.featureSubsetStrategy, ['all', 'onethird', 'sqrt', 'log2'])\
        .build()

      tvs_rf = TrainValidationSplit(estimator=rf,
                                    estimatorParamMaps=paramsGrid_rf,
                                    evaluator=evaluator,
                                    parallelism=2, seed=843).setTrainRatio(0.8)
```

[42]:
```
tvsFitted_rf_G_avg = tvs_rf.fit(train_G_avg)
```

[43]:
```
bestrf_G_avg = tvsFitted_rf_G_avg.bestModel
```

[44]:
```
rmse_rf_G_avg_train = evaluator.evaluate(bestrf_G_avg.transform(train_G_avg),␣
 ↪{evaluator.metricName: "rmse"})
rmse_rf_G_avg_test = evaluator.evaluate(bestrf_G_avg.transform(test_G_avg),␣
 ↪{evaluator.metricName: "rmse"})
print("RMSE for train dataset", rmse_rf_G_avg_train)
print("RMSE for test dataset", rmse_rf_G_avg_test)
```

```
RMSE for train dataset 1.725757416577847
RMSE for test dataset 4.065130320425051
```

The Random Forest outperformed both the Decision Tree and Ridge Regressor at predicted average voter turnout for general election cycles. Our Random Forest model is what we will use for predicting average voter turnout for general election cycles.

Feature importance Now, let's examine how each model places importance on the dataset features. Specifically, we want to understand the interplay between the education level features. We'll extract the feature coefficients learned by each model, and take the subset of education features. By also having the model's trained with income level features, we have been able to better control for the confounding effect income may have had on education level interpretation.

[45]:
```
coefsArray = np.array(bestlr_G_avg.coefficients)
coefsDF_G_avg = pd.DataFrame(coefsArray, columns=['Ridge'])
coefsDF_G_avg = featureCols.merge(coefsDF_G_avg, left_index=True,␣
 ↪right_index=True)

coefsArray = np.array(besttree_G_avg.featureImportances)
coefsDF_2 = pd.DataFrame(coefsArray, columns=['Decision Tree'])
coefsDF_G_avg = coefsDF_G_avg.merge(coefsDF_2, left_index=True,␣
 ↪right_index=True)

coefsArray = np.array(bestrf_G_avg.featureImportances)
coefsDF_2 = pd.DataFrame(coefsArray, columns=['Random Forest'])
coefsDF_G_avg = coefsDF_G_avg.merge(coefsDF_2, left_index=True,␣
 ↪right_index=True)

coefsDF_G_avg['Average'] = (abs(coefsDF_G_avg['Ridge']) +␣
 ↪coefsDF_G_avg['Decision Tree'] + coefsDF_G_avg['Random Forest'])/3

coefsDF_education_G_avg = coefsDF_G_avg[:5].sort_values('Average')
```

The coefficients of the ridge regressor denote that, from the model's perspective, all but the *higher than college* education level have a negative impact, which means the increase in population proportion of other educational levels will lead to the decrease in the general turnout.

[46]:
```
coefsDF_education_G_avg
```

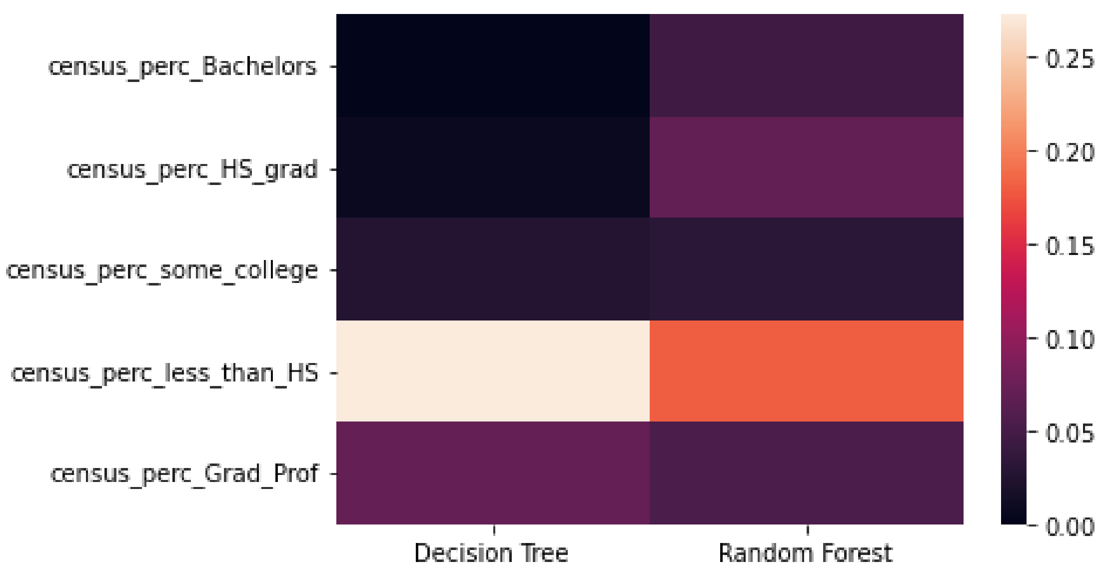
[46]:

	name	Ridge	Decision Tree	Random Forest	Average
3	census_perc_Bachelors	-0.063360	0.000000	0.045002	0.036121
1	census_perc_HS_grad	-0.259428	0.006672	0.068940	0.111680
2	census_perc_some_college	-0.841983	0.025636	0.030758	0.299459
0	census_perc_less_than_HS	-0.688664	0.272283	0.180194	0.380380
4	census_perc_Grad_Prof	1.739241	0.070289	0.053195	0.620909

We further compare feature importances across the tree-based models. For making predictions, the tree-based models place highest feature importance on the *less than high school* education level. For the decision tree, the remaining features aside from *graduate / higher than college* have very low importance in deciding voter turnout. Thus, the two extremes of the education level bins (*less than high school* and *graduate / higher than college*) are most informative. For the random forest, *HS graduate* is the second most important feature, with *graduate / higher than college* and *Bachelors* having some influence and *some college* having almost no influence.

[47]:
```
sns.heatmap(coefsDF_education_G_avg[['Decision Tree', 'Random Forest']],
 ↪yticklabels=coefsDF_education_G_avg['name'])
```

[47]: <AxesSubplot:>



Average RMSE We'll also compute the average RMSE across the 3 models as a comparison for evalutaing how easy or hard this prediction task is relative to the other two.

[48]:
```

```

```
rmse_train_G_avg = (rmse_lr_G_avg_train + rmse_tree_G_avg_train +␣
 ↪rmse_rf_G_avg_train) / 3
rmse_test_G_avg = (rmse_lr_G_avg_test + rmse_tree_G_avg_test +␣
 ↪rmse_rf_G_avg_test) / 3
print("Average RMSE for train dataset", rmse_train_G_avg)
print("Average RMSE for test dataset", rmse_test_G_avg)
```

```
Average RMSE for train dataset 1.959224409481882
Average RMSE for test dataset 6.048645550554297
```

7.2.2 Model for P_avgturnout

Now, we will model average voter turnout across the past 6 primary election cycles.

We will use the same strategy of training and comparing three models – ridge regression, decision tree, and random forest – searching over the same hyperparameter space to extract the best performing model.

Ridge regression

[49]:
```
tvsFitted_lr_P_avg = tvs_lr.fit(train_P_avg)
bestlr_P_avg = tvsFitted_lr_P_avg.bestModel
rmse_lr_P_avg_train = evaluator.evaluate(bestlr_P_avg.transform(train_P_avg),␣
 ↪{evaluator.metricName: "rmse"})
rmse_lr_P_avg_test = evaluator.evaluate(bestlr_P_avg.transform(test_P_avg),␣
 ↪{evaluator.metricName: "rmse"})
print("RMSE for train dataset", rmse_lr_P_avg_train)
print("RMSE for test dataset", rmse_lr_P_avg_test)
```

```
22/05/02 00:40:07 WARN org.apache.spark.ml.util.Instrumentation: [da482ccb]
regParam is zero, which might cause numerical instability and overfitting.
22/05/02 00:40:07 WARN org.apache.spark.ml.util.Instrumentation: [da482ccb]
Cholesky solver failed due to singular covariance matrix. Retrying with Quasi-
Newton solver.
```

```
RMSE for train dataset 3.270620633082699
RMSE for test dataset 4.049467921474852
```

Decision tree

[50]:
```
tvsFitted_tree_P_avg = tvs_tree.fit(train_P_avg)
besttree_P_avg = tvsFitted_tree_P_avg.bestModel
rmse_tree_P_avg_train = evaluator.evaluate(besttree_P_avg.
 ↪transform(train_P_avg), {evaluator.metricName: "rmse"})
rmse_tree_P_avg_test = evaluator.evaluate(besttree_P_avg.transform(test_P_avg),␣
 ↪{evaluator.metricName: "rmse"})
print("RMSE for train dataset", rmse_tree_P_avg_train)
print("RMSE for test dataset", rmse_tree_P_avg_test)
```

```
RMSE for train dataset 1.4984311059005566
RMSE for test dataset 3.1205011395486717
```

Random forest

```
[51]: tvsFitted_rf_P_avg = tvs_rf.fit(train_P_avg)
bestrf_P_avg = tvsFitted_rf_P_avg.bestModel
rmse_rf_P_avg_train = evaluator.evaluate(bestrf_P_avg.transform(train_P_avg),␣
 ↪{evaluator.metricName: "rmse"})
rmse_rf_P_avg_test = evaluator.evaluate(bestrf_P_avg.transform(test_P_avg),␣
 ↪{evaluator.metricName: "rmse"})
print("RMSE for train dataset", rmse_rf_P_avg_train)
print("RMSE for test dataset", rmse_rf_P_avg_test)
```

```
RMSE for train dataset 1.6156642729178048
RMSE for test dataset 3.150916613407327
```

Like the task of predicting voter turnout on general elections, ridge regression was the worst performing model. However, this time the decision tree edged out the random forest model, achieving the lowest RMSE on both the train and test data sets.

Feature importance Now, let's examine how each model places importance on the dataset features. Specifically, we want to understand the interplay between the education level features. We'll extract the feature coefficients learned by each model, and take the subset of education features. By also having the model's trained with income level features, we have been able to better control for the confounding effect income may have had on education level interpretation.

```
[52]: coefsArray = np.array(bestlr_P_avg.coefficients)
coefsDF_P_avg = pd.DataFrame(coefsArray, columns=['Ridge'])
coefsDF_P_avg = featureCols.merge(coefsDF_P_avg, left_index=True,␣
 ↪right_index=True)

coefsArray = np.array(besttree_P_avg.featureImportances)
coefsDF_2 = pd.DataFrame(coefsArray, columns=['Decision Tree'])
coefsDF_P_avg = coefsDF_P_avg.merge(coefsDF_2, left_index=True,␣
 ↪right_index=True)

coefsArray = np.array(bestrf_P_avg.featureImportances)
coefsDF_2 = pd.DataFrame(coefsArray, columns=['Random Forest'])
coefsDF_P_avg = coefsDF_P_avg.merge(coefsDF_2, left_index=True,␣
 ↪right_index=True)

coefsDF_P_avg['Average'] = (abs(coefsDF_P_avg['Ridge']) +␣
 ↪coefsDF_P_avg['Decision Tree'] + coefsDF_P_avg['Random Forest'])/3

coefsDF_education_P_avg = coefsDF_P_avg[:5].sort_values('Average',␣
 ↪ascending=False)
```

high school graduation and *less than high school* have negative impacts, which means the increase in population proportion of these two educational levels will lead to a decrease in primary election voter turnout

[53]:
```
coefsDF_education_P_avg
```

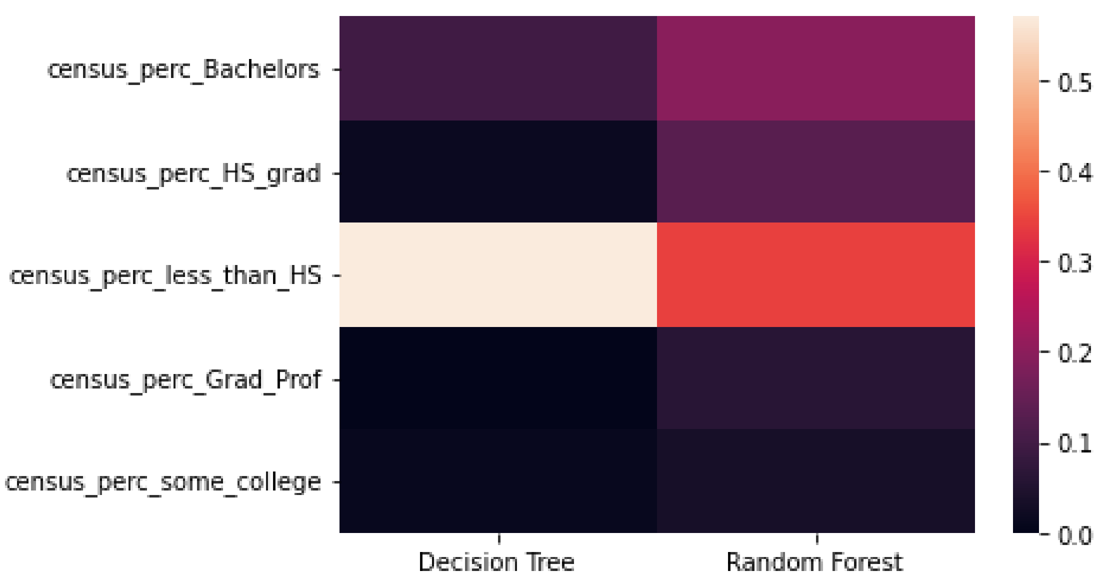
[53]:

	name	Ridge	Decision Tree	Random Forest	Average
3	census_perc_Bachelors	1.405306	0.097491	0.196929	0.566575
1	census_perc_HS_grad	-1.155375	0.016828	0.130252	0.434152
0	census_perc_less_than_HS	-0.023576	0.569469	0.342963	0.312003
4	census_perc_Grad_Prof	0.033312	0.000000	0.061256	0.031523
2	census_perc_some_college	0.017282	0.012821	0.035014	0.021706

For making predictions on primary voter turnout, the tree models again place greatest information gain on *less than HS* education level, followed by the *Bachelors* education level. The magnitude of importance on *less than HS* is much higher though, compared to its magnitude of importance for predicting general election turnout.

[54]:
```
sns.heatmap(coefsDF_education_P_avg[['Decision Tree', 'Random Forest']],␣
↪yticklabels=coefsDF_education_P_avg['name'])
```

[54]: <AxesSubplot:>



Average RMSE Compared to the task of predicting average voter turnout for general election cycles, the three model families achieved a higher aggregate train RMSE for predicting primary election cycle turnout. Nevertheless, they achieved a lower aggregate test RMSE. These results in tandem indicate that the models did not overfit and, thus, were better able to generalize when predicting primary election turnout (compared to general election turnout).

[55]:

```
rmse_train_P_avg = (rmse_lr_P_avg_train + rmse_tree_P_avg_train +␣
↪rmse_rf_P_avg_train) / 3
rmse_test_P_avg = (rmse_lr_P_avg_test + rmse_tree_P_avg_test +␣
↪rmse_rf_P_avg_test) / 3
print("Average RMSE for train dataset", rmse_train_P_avg)
print("Average RMSE for test dataset", rmse_test_P_avg)
```

```
Average RMSE for train dataset 2.1282386706336864
Average RMSE for test dataset 3.4402952248102836
```

7.2.3 Model for G__avgturnout__pres

Now, we will model average voter turnout across the past 3 presidential elections.

We will use the same strategy of training and comparing three models – ridge regression, decision tree, and random forest – searching over the same hyperparameter space to extract the best performing model.

Ridge regression

[56]:
```
tvsFitted_lr_G_avg_pres = tvs_lr.fit(train_G_avg_pres)
bestlr_G_avg_pres = tvsFitted_lr_G_avg_pres.bestModel
rmse_lr_G_avg_pres_train = evaluator.evaluate(bestlr_G_avg_pres.
↪transform(train_G_avg_pres), {evaluator.metricName: "rmse"})
rmse_lr_G_avg_pres_test = evaluator.evaluate(bestlr_G_avg_pres.
↪transform(test_G_avg_pres), {evaluator.metricName: "rmse"})
print("RMSE for train dataset", rmse_lr_G_avg_pres_train)
print("RMSE for test dataset", rmse_lr_G_avg_pres_test)
```

```
22/05/02 00:40:53 WARN org.apache.spark.ml.util.Instrumentation: [4fd9fc1d]
regParam is zero, which might cause numerical instability and overfitting.
22/05/02 00:40:53 WARN org.apache.spark.ml.util.Instrumentation: [4fd9fc1d]
Cholesky solver failed due to singular covariance matrix. Retrying with Quasi-
Newton solver.
```

```
RMSE for train dataset 3.029465248528684
RMSE for test dataset 4.504754292665092
```

Decision tree

[57]:
```
tvsFitted_tree_G_avg_pres = tvs_tree.fit(train_G_avg_pres)
besttree_G_avg_pres = tvsFitted_tree_G_avg_pres.bestModel
rmse_tree_G_avg_pres_train = evaluator.evaluate(besttree_G_avg_pres.
↪transform(train_G_avg_pres), {evaluator.metricName: "rmse"})
rmse_tree_G_avg_pres_test = evaluator.evaluate(besttree_G_avg_pres.
↪transform(test_G_avg_pres), {evaluator.metricName: "rmse"})
print("RMSE for train dataset", rmse_tree_G_avg_pres_train)
print("RMSE for test dataset", rmse_tree_G_avg_pres_test)
```

```
RMSE for train dataset 8.439364330324543e-15
RMSE for test dataset 3.3606722016672195
```

Random forest

[58]:
```
tvsFitted_rf_G_avg_pres = tvs_rf.fit(train_G_avg_pres)
bestrf_G_avg_pres = tvsFitted_rf_G_avg_pres.bestModel
rmse_rf_G_avg_pres_train = evaluator.evaluate(bestrf_G_avg_pres.
 ↪transform(train_G_avg_pres), {evaluator.metricName: "rmse"})
rmse_rf_G_avg_pres_test = evaluator.evaluate(bestrf_G_avg_pres.
 ↪transform(test_G_avg_pres), {evaluator.metricName: "rmse"})
print("RMSE for train dataset", rmse_rf_G_avg_pres_train)
print("RMSE for test dataset", rmse_rf_G_avg_pres_test)
```

```
RMSE for train dataset 1.8120338636109332
RMSE for test dataset 3.8386240690446973
```

We note similar model performance trends to predicting voter turnout on primary elections – decision tree performed best on both train and test data sets, followed by random forest and then the ridge regressor.

Feature importance

[59]:
```
coefsArray = np.array(bestlr_G_avg_pres.coefficients)
coefsDF_G_avg_pres = pd.DataFrame(coefsArray, columns=['Ridge'])
coefsDF_G_avg_pres = featureCols.merge(coefsDF_G_avg_pres, left_index=True,␣
 ↪right_index=True)

coefsArray = np.array(besttree_G_avg_pres.featureImportances)
coefsDF_2 = pd.DataFrame(coefsArray, columns=['Decision Tree'])
coefsDF_G_avg_pres = coefsDF_G_avg_pres.merge(coefsDF_2, left_index=True,␣
 ↪right_index=True)

coefsArray = np.array(bestrf_G_avg_pres.featureImportances)
coefsDF_2 = pd.DataFrame(coefsArray, columns=['Random Forest'])
coefsDF_G_avg_pres = coefsDF_G_avg_pres.merge(coefsDF_2, left_index=True,␣
 ↪right_index=True)

coefsDF_G_avg_pres['Average'] = (abs(coefsDF_G_avg_pres['Ridge']) +␣
 ↪coefsDF_G_avg_pres['Decision Tree'] + coefsDF_G_avg_pres['Random Forest'])/3

coefsDF_education_G_avg_pres = coefsDF_G_avg_pres[:5].sort_values('Average',␣
 ↪ascending=False)
```

higher than college and *Bachelor degree* have positive impacts, which means that an increase in population proportion of these two educational levels may lead to an increase in the turnout of general elections that coincide with a presidential election.

[60]:
```
coefsDF_education_G_avg_pres
```

[60]:

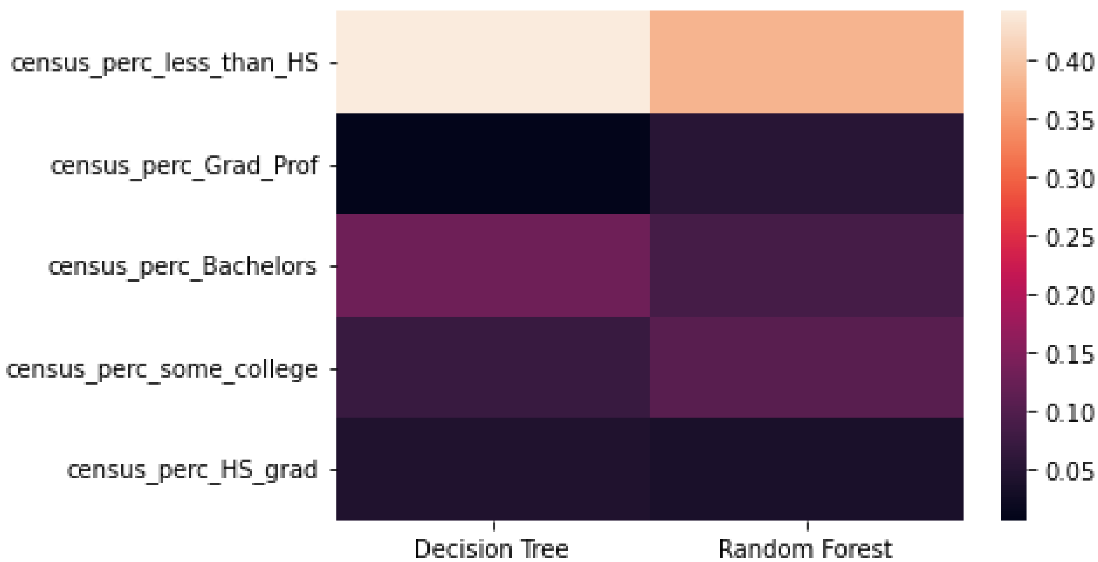
	name	Ridge	Decision Tree	Random Forest	Average
0	census_perc_less_than_HS	-1.341839	0.442099	0.380701	0.721546
4	census_perc_Grad_Prof	1.175311	0.007221	0.053949	0.412160

```
3      census_perc_Bachelors  0.877985        0.129562        0.085387  0.364312
2   census_perc_some_college -0.581186        0.072240        0.106219  0.253215
1         census_perc_HS_grad -0.447931        0.043164        0.037110  0.176068
```

For making predictions on primary voter turnout, the tree models again place greatest information gain on *less than HS* education level. The magnitude of importance on *less than HS* is a little less than its magnitude of importance for predicting primary election turnout.

[61]:
```
sns.heatmap(coefsDF_education_G_avg_pres[['Decision Tree', 'Random Forest']],
    yticklabels=coefsDF_education_G_avg_pres['name'])
```

[61]: <AxesSubplot:>



Average RMSE Compared to the previous two tasks, the aggregate train dataset performance was ordered, from lowest to highest RMSE, general election turnout, presidential election turnout, primary election turnout. The aggregate test dataset performance was ordered, from lowest to highest RMSE, primary election turnout, presidential election turnout, general election turnout. Thus, the models, in aggregate, best generalized to the primary election turnout task, followed by presidential election turnout and then general election turnout.

[62]:
```
rmse_train_G_avg_pres = (rmse_lr_G_avg_pres_train + rmse_tree_G_avg_pres_train
    + rmse_rf_G_avg_pres_train) / 3
rmse_test_G_avg_pres = (rmse_lr_G_avg_pres_test + rmse_tree_G_avg_pres_test +
    rmse_rf_G_avg_pres_test) / 3
print("Average RMSE for train dataset", rmse_train_G_avg_pres)
print("Average RMSE for test dataset", rmse_test_G_avg_pres)
```

```
Average RMSE for train dataset 1.613833037379875
Average RMSE for test dataset 3.9013501877923367
```

7.3 Modeling Conclusions

7.3.1 Feature importance

Recall that we previously looked at feature importance across the three models for each of the three tasks – general election, primary election, and presidential election voter turnout. As a recap, we print the feature importance below for each task.

[63]:
```
coefsDF_G_avg[coefsDF_G_avg['name'].isin(educationCol)]
```

[63]:

	name	Ridge	Decision Tree	Random Forest	Average
0	census_perc_less_than_HS	-0.688664	0.272283	0.180194	0.380380
1	census_perc_HS_grad	-0.259428	0.006672	0.068940	0.111680
2	census_perc_some_college	-0.841983	0.025636	0.030758	0.299459
3	census_perc_Bachelors	-0.063360	0.000000	0.045002	0.036121
4	census_perc_Grad_Prof	1.739241	0.070289	0.053195	0.620909

[64]:
```
coefsDF_P_avg[coefsDF_P_avg['name'].isin(educationCol)]
```

[64]:

	name	Ridge	Decision Tree	Random Forest	Average
0	census_perc_less_than_HS	-0.023576	0.569469	0.342963	0.312003
1	census_perc_HS_grad	-1.155375	0.016828	0.130252	0.434152
2	census_perc_some_college	0.017282	0.012821	0.035014	0.021706
3	census_perc_Bachelors	1.405306	0.097491	0.196929	0.566575
4	census_perc_Grad_Prof	0.033312	0.000000	0.061256	0.031523

[65]:
```
coefsDF_G_avg_pres[coefsDF_G_avg_pres['name'].isin(educationCol)]
```

[65]:

	name	Ridge	Decision Tree	Random Forest	Average
0	census_perc_less_than_HS	-1.341839	0.442099	0.380701	0.721546
1	census_perc_HS_grad	-0.447931	0.043164	0.037110	0.176068
2	census_perc_some_college	-0.581186	0.072240	0.106219	0.253215
3	census_perc_Bachelors	0.877985	0.129562	0.085387	0.364312
4	census_perc_Grad_Prof	1.175311	0.007221	0.053949	0.412160

Regarding the relationship between education level and voter turnout, we saw that an education *higher than college* was associated with positive voter turnout for all three election types. In contrast, education levels *less than high school* and *high school graduate* were both associated with negative voter turnout for all three election types. In the middle, *Bachelors* was positively associated with primary and presidential elections, while *some college* was only positively associated for priamry elections.

Furthermore, an education level of *less than high school* had notable more feature importance for the tree-based models than any other education level, regardless of election cycle. The only influence of election cycle was the magnitude of that feature importance, with it being greatest for Primary election cycles.

In tandem, these findings indicate that Primary election cycle voter turnout is most sensitive to a constituency with higher levels of education. Also, the higher the education level, the greater the positive association with voting – to the point that an education of *higher than college* is positively associated with voter turnout for all election types. On the other hand, having a proportionally higher *less than high school* educated population is a highly important marker of lowered voter turnout for all election types we analyzed.

In general, higher than college have positive impacts on general elections, primary elections and precidential elections. Though bachelors degree have small negative impact on general elections, it have positive impact on the other two elections and have high importance. Thus, in order to encourage people participate in elections, measures should be adopted to encourage residents to go to college. We have following suggestions: - Improve the educational level of basic education and develop students' interest in learning from an early age. - Reduce tuition fees at public universities. - Reduce the interest rate of student loans. - Encourage working people to enroll in part-time undergraduate or graduate programs.

7.3.2 Model applicability

Target variable	Avg RMSE for train	Avg RMSE for test
General turnout	1.96	6.04
Primary turnout	2.13	3.44
General turnout (precidential)	1.61	3.90

Though general turnout have relatively small average RMSE, it has the highest average RMSE for test, which means the models do not generalize well. Primary turnout have the highest average RMSE for train but lowest average RMSE for test. General turnout (presidential) have the lowest average RMSE for train and moderate average RMSE for test. In aggregate, the models were less liable to overfit on the primary turnout task.

Because our attempts are still few, it is not very rigorous to draw direct conclusions about which variable is more appropriate to predict with education level. However, from our results, the primary and general elections (presidential) may be more worthy of further study.

7.4 Modeling Limitations

- Because we only considered NY and MA, and our models are biult on county-level, the sample size is limited.
- The average turnouts are calculated based on the the elections in the past six years. There is no guarantee that we will see the same trend in the future.

If we got a chance of future exploration, there are few ways to improve our model.

Improve models: - Larger sample size. - More gridsearch parameters.

Increase sample size: - Include more states in our dataset. - Find data on the demographic distribution of education levels for each county for the past six years and combine it with our existing voter turnout for each counry for the past six years, so that our sample size becomes 6 * the total number of couties.

8 Conclusion

The impact of education levels on election turnouts.
- Higher overall education levels of counties lead to higher voter turnout, and education levels have

a greater impact on primary election turnout.
- Specificaly, for general election turnout, *some college*, *bachelors* and *grad,prof* have positive impacts, while *less than high school* and *high school* have negative impacts. For primary election turnout, *bachelors* and *grad,prof* have larger positive impacts, while *some college*, *less than high school* and *high school* have negative impacts.

We do not think income would exacerbate the impact of education levels on election turnouts.
- Higher overall education will bring higher income level for a county.
- However, all the income levels have negative impacts on general election turnouts, and all the income levels have positive impacts on primary election turnouts. And the overall income level of counties has similar impacts on general and primary election turnouts.
- If higher education is what increases turnout through higher income, then higher income should result in higher turnout, and the correlation between overall district income levels and primary elections should be greater. But this is not the case.

Possible next steps:
- Investigate on individual-level
- Combine education with other factors, like donating actions, interest in religious inspirational, if the individual is an investor, etc., to find out the approach of the education influencing the election turnout.
- Integrate additional data from recent elections, such as the 2020 general (presidential) elections
- Investigate whether voter turnout behavior and its relation to education level is dependent on state or region (e.g., West Coast, East Coast, Midwest, South)

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