Political_Project

March 21, 2024

[1]:
```
from pyspark.sql import SparkSession
spark = SparkSession \
.builder \
.appName("Read Voter File Data") \
.getOrCreate()

df = (
spark.read
    .format("parquet")
    .option("header", "true")
    .option("inferSchema", "true")
    .load("gs://winter-2024-voter-file/VM2Uniform/VM2Uniform--PA--2021-05-20")
)
# 8359764 rows befor cleaning
```

```
24/03/18 21:41:22 WARN SparkSession: Using an existing Spark session; only
runtime SQL configurations will take effect.
```

The first step is to clean the data. We selected the columns we would use later and remove the null data. For simplicity, we would only focus on the Democratic and Republican party and ignore all other party voters.

[2]:
```
df = df[df.Voters_Active == "A"]
```

[3]:
```
df = df[df.Voters_VotingPerformanceEvenYearGeneral != "Not Eligible"]
```

[4]:
```
df = df.filter(df["CommercialData_EstimatedHHIncomeAmount"].isNotNull())
```

[5]:
```
df = df.filter(df["CommercialData_ISPSA"].isNotNull())
```

[6]:
```
df = df.filter(df["Voters_Age"].isNotNull())
```

[7]:
```
df = df.filter(df["EthnicGroups_EthnicGroup1Desc"].isNotNull())
```

[8]:
```
df = df[(df.Parties_Description == "Republican") | (df.Parties_Description ==␣
↪"Democratic")]
```

[9]:
```
df = df.filter(df["CommercialData_EstHomeValue"].isNotNull())
```

[10]:
```
df.count()
# after cleaning still over 5 million rows, data is enough
```

[10]: 5699424

The next step is to turn the data from string to intergers and and dummy variables for categorical data.

[11]:
```
import pyspark.sql.functions as f
from pyspark.sql.types import IntegerType
df = df.withColumn('Participation', f.
 ↪regexp_replace('Voters_VotingPerformanceEvenYearGeneral', '[%]', '').
 ↪cast('int'))
df = df.withColumn('Income', f.
 ↪regexp_replace('CommercialData_EstimatedHHIncomeAmount', '[$]', '').
 ↪cast('int'))
df = df.withColumn('Home_Value', f.
 ↪regexp_replace('CommercialData_EstHomeValue', '[$]', '').cast('int'))
df = df.withColumn('Age', df.Voters_Age.cast('int'))
df = df.withColumn('Family_Head_Count', df.Residence_Families_HHCount.
 ↪cast('int'))
df = df.withColumn('ISPSA', df.CommercialData_ISPSA.cast('int'))
```

[12]:
```
df = df.na.fill("no")
```

[13]:
```
from pyspark.ml.feature import StringIndexer
df = StringIndexer(inputCol="Parties_Description",outputCol="Party_index").
 ↪fit(df).transform(df)
df =␣
 ↪StringIndexer(inputCol="MaritalStatus_Description",outputCol="Marital_index").
 ↪fit(df).transform(df)
df =␣
 ↪StringIndexer(inputCol="EthnicGroups_EthnicGroup1Desc",outputCol="Ethnic_index").
 ↪fit(df).transform(df)
df = StringIndexer(inputCol="CommercialDataLL_Gun_Owner",outputCol="Gun_index").
 ↪fit(df).transform(df)
df =␣
 ↪StringIndexer(inputCol="CommercialDataLL_Home_Owner_Or_Renter",outputCol="House_index").
 ↪fit(df).transform(df)
```

[14]:
```
from pyspark.ml.feature import OneHotEncoder
df = OneHotEncoder(inputCols=['Party_index'], outputCols=['Party_dummy']).
 ↪fit(df).transform(df)
```

```
df = OneHotEncoder(inputCols=['Marital_index'], outputCols=['Marital_dummy']).
 ↪fit(df).transform(df)
df = OneHotEncoder(inputCols=['Ethnic_index'], outputCols=['Ethnic_dummy']).
 ↪fit(df).transform(df)
df = OneHotEncoder(inputCols=['Gun_index'], outputCols=['Gun_ownership_dummy']).
 ↪fit(df).transform(df)
df = OneHotEncoder(inputCols=['House_index'],␣
 ↪outputCols=['Home_ownership_dummy']).fit(df).transform(df)
```

[15]:
```
df = df.withColumn('Party', df.Parties_Description)
df = df.withColumn('Marital', df.MaritalStatus_Description)
df = df.withColumn('Ethnic', df.EthnicGroups_EthnicGroup1Desc)
df = df.withColumn('Gun_ownership', df.CommercialDataLL_Gun_Owner)
df = df.withColumn('Home_ownership', df.CommercialDataLL_Home_Owner_Or_Renter)
```

[16]:
```
voter_df = df["Participation", "Party", "Party_dummy", "Age", "Marital",␣
 ↪"Marital_dummy", "Family_Head_Count", "Ethnic", "Ethnic_dummy",
             "Income", "ISPSA", "Gun_ownership", "Gun_ownership_dummy",␣
 ↪"Home_ownership", "Home_ownership_dummy", "Home_value"]
```

[17]:
```
voter_df.show()
```

```
+-------------+----------+-------------+---+---------------+-------------+------
-----------+-------------------+-------------+------+-----+-------------+------
-------------+----------------+--------------------+----------+
|Participation|     Party|  Party_dummy|Age|
Marital|Marital_dummy|Family_Head_Count|              Ethnic|
Ethnic_dummy|Income|ISPSA|Gun_ownership|Gun_ownership_dummy|
Home_ownership|Home_ownership_dummy|Home_value|
+-------------+----------+-------------+---+---------------+-------------+------
-----------+-------------------+-------------+------+-----+-------------+------
-------------+----------------+--------------------+----------+
|          100|Democratic|(1,[0],[1.0])| 50|Non-Traditional|    (2,[],[])|
2|Hispanic and Port…|(4,[2],[1.0])| 75525|    3|           no|
(1,[0],[1.0])|              no|       (2,[1],[1.0])|    170057|
|          100|Republican|    (1,[],[])| 36|             no|(2,[0],[1.0])|
2|            European|(4,[0],[1.0])| 75525|    3|           no|
(1,[0],[1.0])|              no|       (2,[1],[1.0])|    170057|
|           28|Republican|    (1,[],[])| 65|             no|(2,[0],[1.0])|
1|            European|(4,[0],[1.0])|112000|    3|           no|
(1,[0],[1.0])|              no|       (2,[1],[1.0])|    115554|
|          100|Republican|    (1,[],[])| 31|        Married|(2,[1],[1.0])|
2|            European|(4,[0],[1.0])| 64000|    3|           no|
(1,[0],[1.0])|Likely Homeowner|       (2,[0],[1.0])|    135801|
|           85|Republican|    (1,[],[])| 34|        Married|(2,[1],[1.0])|
2|            European|(4,[0],[1.0])| 64000|    3|           no|
```

```
(1,[0],[1.0])|Likely Homeowner|       (2,[0],[1.0])|    135801|
|          66|Republican|    (1,[],[])| 64|            no|(2,[0],[1.0])|
1|              Other|(4,[3],[1.0])| 14000|    3|           no|
(1,[0],[1.0])|Likely Homeowner|       (2,[0],[1.0])|    160863|
|           0|Democratic|(1,[0],[1.0])| 29|       Married|(2,[1],[1.0])|
2|           European|(4,[0],[1.0])| 56000|    3|           no|
(1,[0],[1.0])|   Likely Renter|           (2,[],[])|    191749|
|           0|Democratic|(1,[0],[1.0])| 31|       Married|(2,[1],[1.0])|
2|           European|(4,[0],[1.0])| 56000|    3|           no|
(1,[0],[1.0])|   Likely Renter|           (2,[],[])|    191749|
|          50|Republican|    (1,[],[])| 37|       Married|(2,[1],[1.0])|
2|           European|(4,[0],[1.0])| 60000|    3|           no|
(1,[0],[1.0])|   Likely Renter|           (2,[],[])|    131338|
|          50|Republican|    (1,[],[])| 32|       Married|(2,[1],[1.0])|
2|           European|(4,[0],[1.0])| 60000|    3|           no|
(1,[0],[1.0])|   Likely Renter|           (2,[],[])|    131338|
|         100|Democratic|(1,[0],[1.0])| 44|Non-Traditional|    (2,[],[])|
2|           European|(4,[0],[1.0])| 80000|    3|           no|
(1,[0],[1.0])|              no|       (2,[1],[1.0])|    154219|
|          66|Republican|    (1,[],[])| 75|            no|(2,[0],[1.0])|
2|           European|(4,[0],[1.0])| 64000|    3|           no|
(1,[0],[1.0])|Likely Homeowner|       (2,[0],[1.0])|    227966|
|          50|Democratic|(1,[0],[1.0])| 33|            no|(2,[0],[1.0])|
2|           European|(4,[0],[1.0])| 75525|    3|           no|
(1,[0],[1.0])|              no|       (2,[1],[1.0])|    170057|
|         100|Democratic|(1,[0],[1.0])| 54|            no|(2,[0],[1.0])|
1|           European|(4,[0],[1.0])| 20000|    3|           no|
(1,[0],[1.0])|   Likely Renter|           (2,[],[])|     85239|
|         100|Republican|    (1,[],[])| 68|       Married|(2,[1],[1.0])|
2|Likely African-Am…|(4,[1],[1.0])| 98000|    3|           no|
(1,[0],[1.0])|Likely Homeowner|       (2,[0],[1.0])|    117293|
|         100|Republican|    (1,[],[])| 64|       Married|(2,[1],[1.0])|
2|Likely African-Am…|(4,[1],[1.0])| 98000|    3|           no|
(1,[0],[1.0])|Likely Homeowner|       (2,[0],[1.0])|    117293|
|          14|Republican|    (1,[],[])| 62|            no|(2,[0],[1.0])|
1|              Other|(4,[3],[1.0])|109000|    3|           no|
(1,[0],[1.0])|              no|       (2,[1],[1.0])|    195168|
|          40|Republican|    (1,[],[])| 33|            no|(2,[0],[1.0])|
1|           European|(4,[0],[1.0])| 90000|    3|           no|
(1,[0],[1.0])|Likely Homeowner|       (2,[0],[1.0])|    160259|
|          28|Democratic|(1,[0],[1.0])| 48|            no|(2,[0],[1.0])|
1|Hispanic and Port…|(4,[2],[1.0])|  9000|    3|           no|
(1,[0],[1.0])|Likely Homeowner|       (2,[0],[1.0])|    227164|
|          66|Republican|    (1,[],[])| 25|            no|(2,[0],[1.0])|
2|           European|(4,[0],[1.0])|110000|    3|           no|
(1,[0],[1.0])|   Likely Renter|           (2,[],[])|    125959|
+------------+----------+-------------+---+---------------+-------------+------
-----------+------------------+-------------+------+-----+-----------+------
```

```
-------------+---------------+-------------------+----------+
only showing top 20 rows
```

The following is some basic relationship between different variables and the difference in voter turnout between different groups.

[18]:
```
voter_df.groupBy("Party").agg({"Participation":"mean"}).show()
```

```
[Stage 20:=====================================================>   (14 + 1) / 15]

+----------+------------------+
|     Party|avg(Participation)|
+----------+------------------+
|Republican| 76.69780052985456|
|Democratic| 73.29477427160174|
+----------+------------------+
```

[20]:
```
voter_df.groupBy("Marital").agg({"Participation":"mean"}).show()
```

```
[Stage 26:=====================================================>   (14 + 1) / 15]

+---------------+------------------+
|        Marital|avg(Participation)|
+---------------+------------------+
|        Married| 82.22929872604095|
|Non-Traditional| 72.62860598501385|
|             no| 69.68580665982662|
+---------------+------------------+
```

[21]:
```
voter_df.groupBy("Family_Head_Count").agg({"Participation":"mean"}).show()
```

```
[Stage 29:=================================================>       (13 + 2) / 15]

+-----------------+------------------+
|Family_Head_Count|avg(Participation)|
+-----------------+------------------+
|                1| 68.16177561875418|
|                6|  77.9916268684488|
|                3| 77.24116470634826|
|                5| 78.94041599769955|
|                9| 76.77056277056278|
|                4| 79.47237857296057|
|                8| 74.22630834512023|
|                7| 77.77879403794039|
|                2| 77.12837937866307|
```

```
|               10| 79.48051948051948|
+-----------------+------------------+
```

[22]:
```python
voter_df.groupBy("Ethnic").agg({"Participation":"mean"}).show()
```

```
[Stage 32:================================================>       (13 + 2) / 15]

+--------------------+------------------+
|              Ethnic|avg(Participation)|
+--------------------+------------------+
|East and South Asian| 70.24009666218545|
|            European| 76.56557474400681|
|               Other| 74.30369050910892|
|Likely African-Am…| 69.37868413470501|
|Hispanic and Port…| 62.28174037089872|
+--------------------+------------------+
```

[23]:
```python
voter_df.groupBy("Gun_ownership").agg({"Participation":"mean"}).show()
```

```
[Stage 35:====================================================>   (14 + 1) / 15]

+-------------+------------------+
|Gun_ownership|avg(Participation)|
+-------------+------------------+
|          Yes|  83.4959197445661|
|           no| 73.42333385419536|
+-------------+------------------+
```

[24]:
```python
voter_df.groupBy("Home_ownership").agg({"Participation":"mean"}).show()
```

```
[Stage 38:====================================================>   (14 + 1) / 15]

+----------------+------------------+
|  Home_ownership|avg(Participation)|
+----------------+------------------+
|   Likely Renter| 66.09505323565531|
|Likely Homeowner| 80.02774989588386|
|              no| 68.63014813545594|
+----------------+------------------+
```

[25]:
```python
voter_df.groupBy("Party").agg({"Age":"mean"}).show()
```

```
[Stage 41:=====================================================>   (14 + 1) / 15]
```

```
+----------+------------------+
|     Party|          avg(Age)|
+----------+------------------+
|Republican|53.807299120873026|
|Democratic| 51.22940515051766|
+----------+------------------+
```

[26]:
```python
voter_df.groupBy("Party").agg({"Family_Head_Count":"mean"}).show()
```

```
[Stage 44:=================================================>       (13 + 2) / 15]
```

```
+----------+----------------------+
|     Party|avg(Family_Head_Count)|
+----------+----------------------+
|Republican|    2.1686906330937603|
|Democratic|    2.0107762941740854|
+----------+----------------------+
```

[27]:
```python
voter_df.groupBy("Party").agg({"Income":"mean"}).show()
```

```
[Stage 47:=====================================================>   (14 + 1) / 15]
```

```
+----------+-----------------+
|     Party|      avg(Income)|
+----------+-----------------+
|Republican| 97532.8201378169|
|Democratic|86888.60247455402|
+----------+-----------------+
```

[28]:
```python
voter_df.groupBy("Party").agg({"ISPSA":"mean"}).show()
```

```
[Stage 50:=====================================================>   (14 + 1) / 15]
```

```
+----------+-----------------+
|     Party|       avg(ISPSA)|
+----------+-----------------+
|Republican| 4.85430025269344|
|Democratic|4.646526466715416|
+----------+-----------------+
```

[29]:
```
voter_df.groupBy("Party").agg({"Home_value":"mean"}).show()
```

```
[Stage 53:==================================================>      (13 + 2) / 15]

+----------+------------------+
|     Party|   avg(Home_value)|
+----------+------------------+
|Republican|261562.66257466158|
|Democratic| 235215.0307663117|
+----------+------------------+
```

[30]:
```
voter_df.groupBy("Party", "Marital").agg({"Participation":"mean"}).show()
```

```
[Stage 56:======================================================>  (14 + 1) / 15]

+----------+---------------+------------------+
|     Party|        Marital|avg(Participation)|
+----------+---------------+------------------+
|Democratic|             no| 68.87859326894748|
|Republican|             no|   70.964086019238|
|Republican|Non-Traditional| 71.21811856210873|
|Democratic|        Married| 81.67749430804781|
|Republican|        Married| 82.63206278026905|
|Democratic|Non-Traditional| 73.52018407481432|
+----------+---------------+------------------+
```

[31]:
```
voter_df.groupBy("Party", "Ethnic").agg({"Participation":"mean"}).show()
```

```
[Stage 59:======================================================>  (14 + 1) / 15]

+----------+--------------------+------------------+
|     Party|              Ethnic|avg(Participation)|
+----------+--------------------+------------------+
|Democratic|Likely African-Am…| 69.60037224971926|
|Republican|Hispanic and Port…| 65.78019204548751|
|Democratic|East and South Asian| 70.57840221156874|
|Republican|Likely African-Am…| 59.53708262809663|
|Republican|               Other|  75.2919512195122|
|Democratic|            European|  75.7735025552301|
|Republican|            European| 77.23612289331768|
|Republican|East and South Asian| 69.42347111161166|
|Democratic|               Other| 73.65716382822556|
|Democratic|Hispanic and Port…| 61.25052802599512|
+----------+--------------------+------------------+
```

[32]:

```
voter_df.groupBy("Party","Gun_ownership").agg({"Participation":"mean"}).show()
```

```
[Stage 62:=================================================>       (13 + 2) / 15]

+----------+-------------+------------------+
|     Party|Gun_ownership|avg(Participation)|
+----------+-------------+------------------+
|Republican|          Yes| 83.81867004715264|
|Democratic|          Yes| 83.06466685169342|
|Democratic|           no| 72.03844022661764|
|Republican|           no| 75.16185222597733|
+----------+-------------+------------------+
```

[33]:

```
voter_df.groupBy("Party","Home_ownership").agg({"Participation":"mean"}).show()
```

```
[Stage 65:=====================================================>   (14 + 1) / 15]

+----------+----------------+------------------+
|     Party|  Home_ownership|avg(Participation)|
+----------+----------------+------------------+
|Democratic|              no| 67.01023907092306|
|Democratic|Likely Homeowner| 79.64959561379086|
|Republican|              no| 70.64406190379682|
|Democratic|   Likely Renter| 65.52146273324523|
|Republican|   Likely Renter|  67.4356928302955|
|Republican|Likely Homeowner| 80.37788677503364|
+----------+----------------+------------------+
```

[34]:

```
import pandas as pd
sample_df = voter_df.sample(withReplacement=False, fraction=0.0001)
sample_df = sample_df.toPandas()
```

[35]:

```
sample_df
```

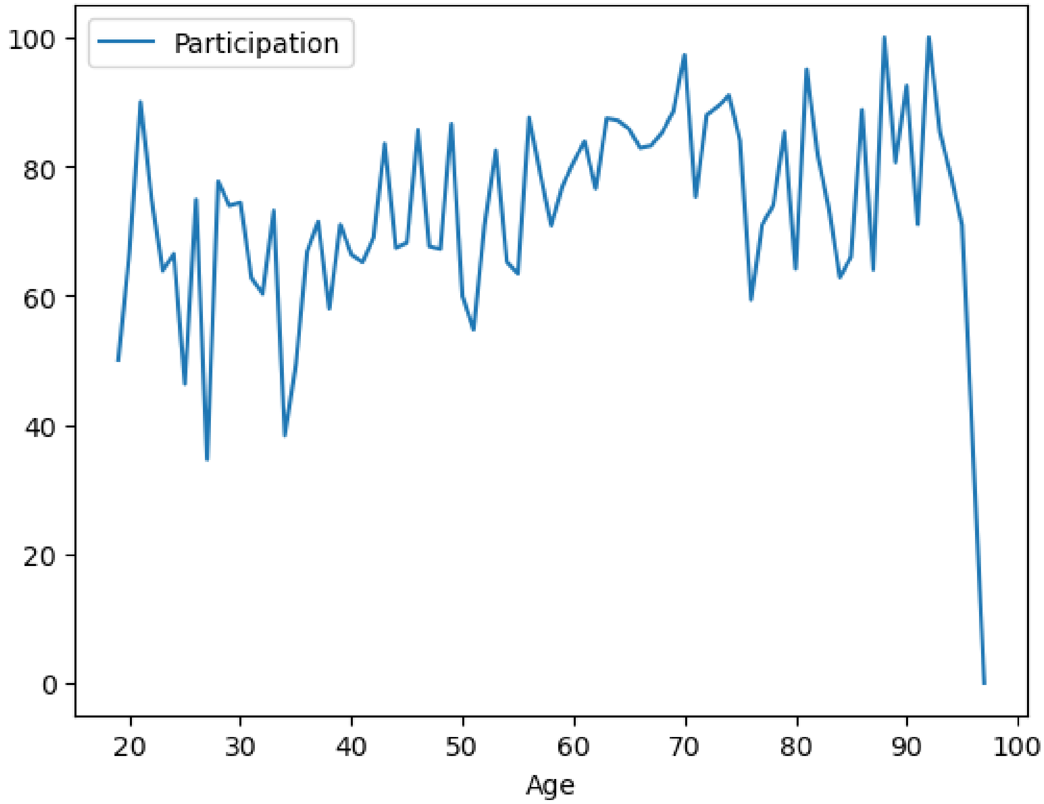
[35]:

```
     Participation       Party Party_dummy  Age         Marital  \
0                0  Republican       (0.0)   32         Married
1               28  Republican       (0.0)   61         Married
2               42  Republican       (0.0)   42         Married
3              100  Republican       (0.0)   87         Married
4              100  Republican       (0.0)   61         Married
..             …           …          …    …              …
```

```
555              0  Democratic      (1.0)   19             no
556            100  Democratic      (1.0)   33             no
557             50  Democratic      (1.0)   42             no
558            100  Democratic      (1.0)   35  Non-Traditional
559            100  Republican      (0.0)   73          Married

    Marital_dummy  Family_Head_Count                   Ethnic  \
0      (0.0, 1.0)                  2                 European
1      (0.0, 1.0)                  2                 European
2      (0.0, 1.0)                  3                 European
3      (0.0, 1.0)                  2                 European
4      (0.0, 1.0)                  2                 European
..            …                  …                      …
555    (1.0, 0.0)                  5                 European
556    (1.0, 0.0)                  1  Hispanic and Portuguese
557    (1.0, 0.0)                  2  Hispanic and Portuguese
558    (0.0, 0.0)                  2  Hispanic and Portuguese
559    (0.0, 1.0)                  3     East and South Asian

              Ethnic_dummy  Income  ISPSA Gun_ownership Gun_ownership_dummy  \
0    (1.0, 0.0, 0.0, 0.0)  136000      5            no               (1.0)
1    (1.0, 0.0, 0.0, 0.0)   45000      2            no               (1.0)
2    (1.0, 0.0, 0.0, 0.0)   94000      5            no               (1.0)
3    (1.0, 0.0, 0.0, 0.0)   35000      3            no               (1.0)
4    (1.0, 0.0, 0.0, 0.0)   34000      2            no               (1.0)
..                     …       …    …            …                  …
555  (1.0, 0.0, 0.0, 0.0)  111000      2            no               (1.0)
556  (0.0, 0.0, 1.0, 0.0)   56000      7            no               (1.0)
557  (0.0, 0.0, 1.0, 0.0)   82000      2            no               (1.0)
558  (0.0, 0.0, 1.0, 0.0)   49582      0            no               (1.0)
559  (0.0, 0.0, 0.0, 0.0)   88586      6           Yes               (0.0)

       Home_ownership Home_ownership_dummy  Home_value
0    Likely Homeowner           (1.0, 0.0)      298764
1       Likely Renter           (0.0, 0.0)      111183
2    Likely Homeowner           (1.0, 0.0)      249279
3    Likely Homeowner           (1.0, 0.0)      237500
4                  no           (0.0, 1.0)       57340
..                …                  …         …
555  Likely Homeowner           (1.0, 0.0)      341385
556     Likely Renter           (0.0, 0.0)      401048
557  Likely Homeowner           (1.0, 0.0)       98268
558                no           (0.0, 1.0)       78648
559  Likely Homeowner           (1.0, 0.0)      330782

[560 rows x 16 columns]
```

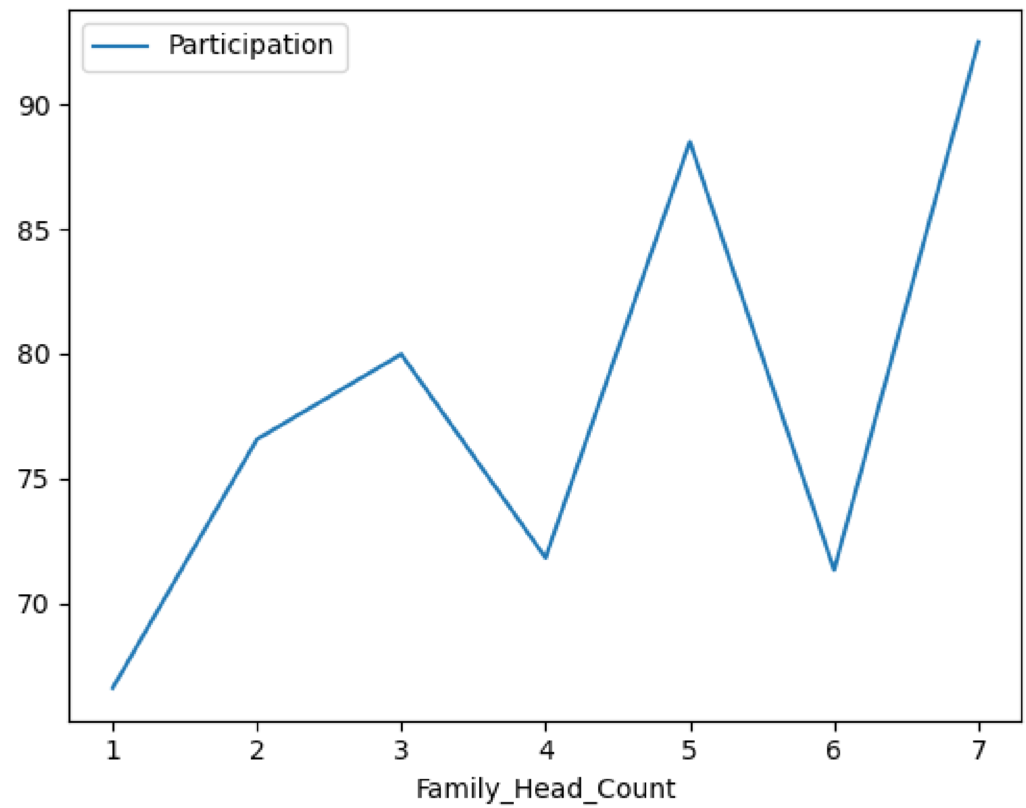
[36]:
```
sample_df.groupby(by=["Age"])[['Participation']].mean().plot()
```

[36]: <AxesSubplot:xlabel='Age'>



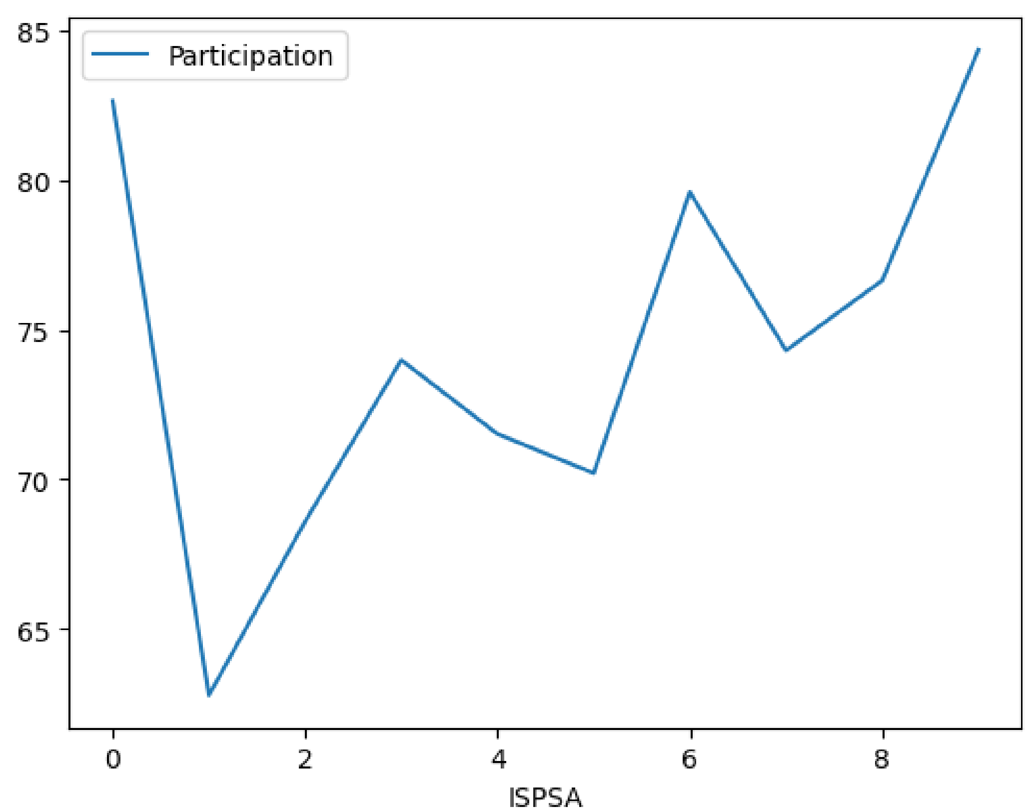
[37]:
```
sample_df.groupby(by=["Family_Head_Count"])[['Participation']].mean().plot()
```

[37]: <AxesSubplot:xlabel='Family_Head_Count'>

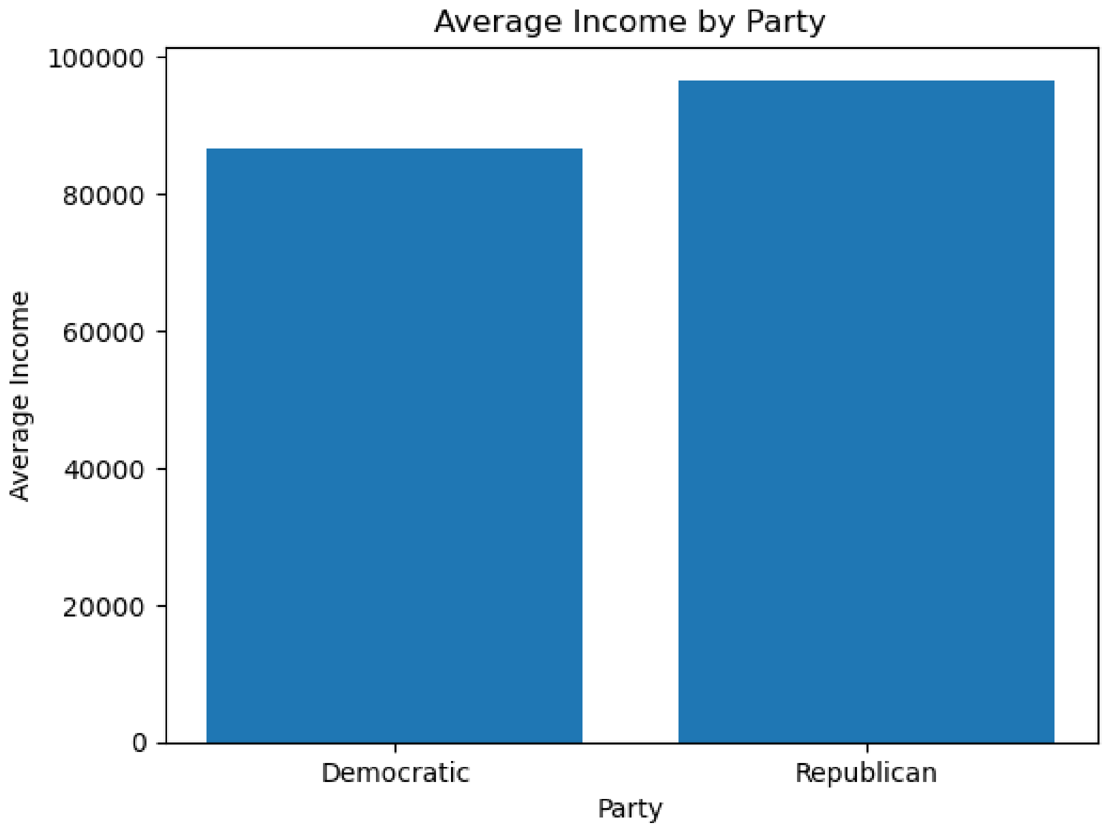


[38]:
```
sample_df.groupby(by=["ISPSA"])[['Participation']].mean().plot()
```

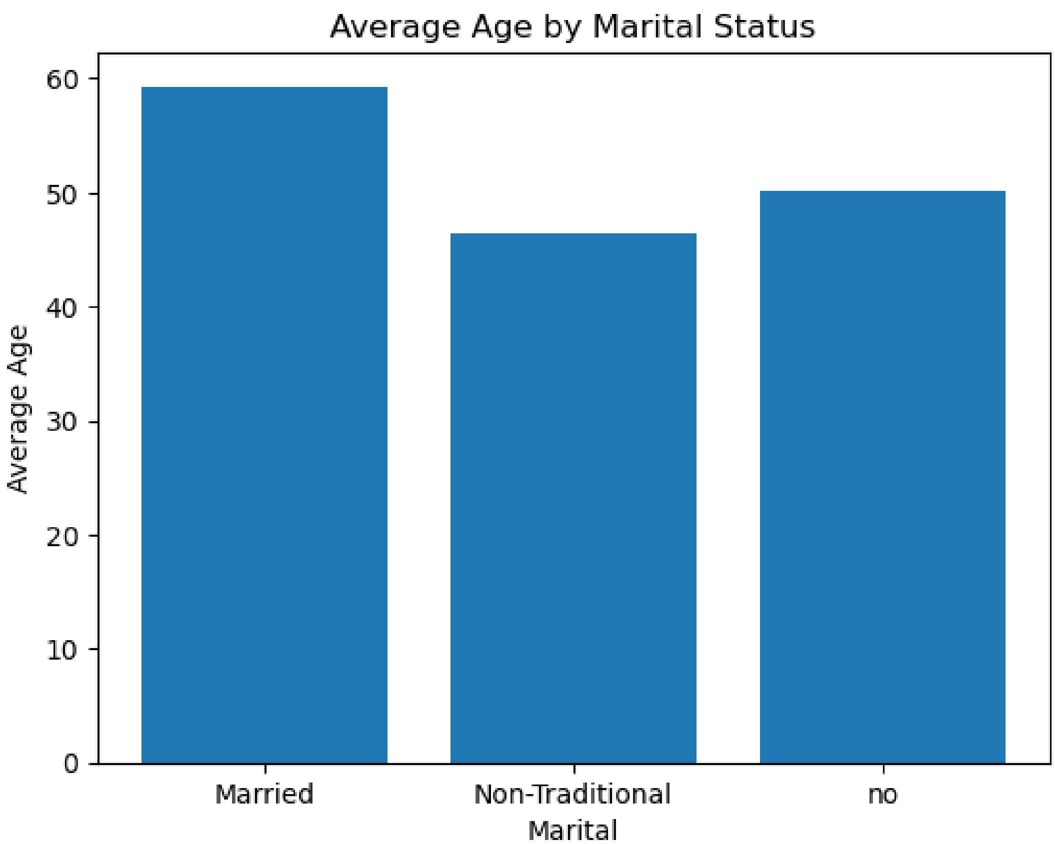
[38]: <AxesSubplot:xlabel='ISPSA'>



[39]:
```
import matplotlib.pyplot as plt
sample_mean = sample_df.groupby('Party')['Income'].mean().reset_index()

plt.bar(sample_mean['Party'], sample_mean['Income'])
plt.xlabel('Party')
plt.ylabel('Average Income')
plt.title('Average Income by Party')
plt.show()
```



[40]:
```
sample_mean2 = sample_df.groupby('Marital')['Age'].mean().reset_index()

plt.bar(sample_mean2['Marital'], sample_mean2['Age'])
plt.xlabel('Marital')
plt.ylabel('Average Age')
plt.title('Average Age by Marital Status')
plt.show()
```



[41]:
```
from pyspark.ml.regression import LinearRegression
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.feature import VectorAssembler

assembler = VectorAssembler(inputCols=[
    'Party_dummy', 'Age', 'Marital_dummy', 'Family_Head_Count', 'Ethnic_dummy',␣
 ↪'Income', 'ISPSA', 'Gun_ownership_dummy', \
    'Home_ownership_dummy'], outputCol='New Data')

new_sample_df = sample_df.drop(columns=['Party', 'Marital', 'Ethnic',␣
 ↪'Gun_ownership', 'Home_ownership', 'Home_value'])
new_sample = spark.createDataFrame(new_sample_df)
new_df = assembler.transform(new_sample)
sample_train, sample_test = new_df.randomSplit([0.8, 0.2], seed=134)

regression = LinearRegression(labelCol='Participation', featuresCol = 'New␣
 ↪Data')
regression = regression.fit(sample_train)
prediction = regression.transform(sample_test)
```

```
rmse_lr = RegressionEvaluator(labelCol='Participation').evaluate(prediction)
r2_lr = RegressionEvaluator(labelCol='Participation', metricName='r2').
 ↪evaluate(prediction)
mse_lr = RegressionEvaluator(labelCol='Participation', metricName='mse').
 ↪evaluate(prediction)

print("RMSE for Linear Regression: %g" % rmse_lr)
print("R-squared for Linear Regression: %g" % r2_lr)
print("Mean Squared Error for Linear Regression: %g" % mse_lr)
print("Coefficients:", regression.coefficients)
```

```
24/03/18 21:49:07 WARN Instrumentation: [3316b22e] regParam is zero, which might
cause numerical instability and overfitting.
```

```
RMSE for Linear Regression: 26.624
R-squared for Linear Regression: 0.0658797
Mean Squared Error for Linear Regression: 708.836
Coefficients: [2.100842824396812,0.2699272243735195,-
3.728072524431893,1.6034823079917722,2.952448673768281,-2.643654786420981,-
1.060829480730093,-5.383568373666282,0.11619231393012146,5.744554822154949e-
05,0.40770005053328373,-4.295334536995873,7.260674232245189,7.4951196766424015]
```

[69]:
```
from pyspark.ml.regression import RandomForestRegressor

rf = RandomForestRegressor(labelCol='Participation', featuresCol='New Data',␣
 ↪numTrees = 10)
rf_model = rf.fit(sample_train)
rf_predictions = rf_model.transform(sample_test)

rmse_rf = RegressionEvaluator(labelCol='Participation').evaluate(rf_predictions)
r2_rf = RegressionEvaluator(labelCol='Participation', metricName='r2').
 ↪evaluate(rf_predictions)
mse_rf = RegressionEvaluator(labelCol='Participation', metricName='mse').
 ↪evaluate(rf_predictions)

print("RMSE for Random Forest Regression: %g" % rmse_rf)
print("R-squared for Random Forest Regression: %g" % r2_rf)
print("Mean Squared Error for Random Forest Regression: %g" % mse_rf)
print("Features of Importance:", rf_model.featureImportances)
```

```
RMSE for Random Forest Regression: 26.3327
R-squared for Random Forest Regression: 0.0862076
Mean Squared Error for Random Forest Regression: 693.41
Features of Importance: (14,[0,1,2,3,4,5,6,7,8,9,10,11,12,13],[0.030755643209142
904,0.3005685131366359,0.05293001415432713,0.025152962135343765,0.05668594233149
421,0.01035365630342367,0.02329664794458962,0.010385645109989034,0.0269395904554
```

```
24968,0.23608874526377366,0.12764596053267033,0.03769152645516131,0.039790064073
32447,0.02171508889469915])
```

[70]:
```
from pyspark.ml.regression import DecisionTreeRegressor

dt = DecisionTreeRegressor(labelCol='Participation', featuresCol='New Data')
dt_model = dt.fit(sample_train)
dt_predictions = dt_model.transform(sample_test)

rmse_dt = RegressionEvaluator(labelCol='Participation').evaluate(dt_predictions)
r2_dt = RegressionEvaluator(labelCol='Participation', metricName='r2').
 ↪evaluate(dt_predictions)
mse_dt = RegressionEvaluator(labelCol='Participation', metricName='mse').
 ↪evaluate(dt_predictions)

print("RMSE for Decision Tree Regression: %g" % rmse_dt)
print("R-squared for Decision Tree Regression: %g" % r2_dt)
print("Mean Squared Error for Decision Tree Regression: %g" % mse_dt)
print("Features of Importance:", dt_model.featureImportances)
```

```
RMSE for Decision Tree Regression: 30.3093
R-squared for Decision Tree Regression: -0.21062
Mean Squared Error for Decision Tree Regression: 918.651
Features of Importance: (14,[0,1,2,4,8,9,10,11,12,13],[0.02463752137773786,0.287
0299830578729,0.05650216874212615,0.13606264954351635,0.0012318760688868932,0.36
2103182494346,0.08056823815953423,0.021824861702102873,0.022155512013000485,0.00
7884006840876118])
```

[68]:
```
corr = sample_df.corr()
corr.style.background_gradient(cmap='coolwarm')
```

[68]: <pandas.io.formats.style.Styler at 0x7f43343dff10>

We can see the strongest correlation with participation is age and then home value. But overall, the correlation is not that significant, meaning the factors are not that decisive in determining the voter turnout.

[ ]:
```
```