Final Project

March 23, 2023

0.1 Cross-Analyzing Voter Turnout & Party Traits in Alaska & Washington D.C.

0.1.1 PSTAT 135: Group Assignment 1

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We are exploring voter traits, such as gender, gun ownership, marital status, etc, to see if there is any correlation between registered voter party and these attributes. We hope this wiil help enhance our understanding of the voter demographics in Alaska and Washington, as well as how these populations compare and differ. Furthermore, we hope to also implement a variety of models in order to classify their registered party and see which qualities were important in prediction.

[154]:
```
# Starting a spark session
```

[155]:
```
from pyspark.sql import SparkSession
spark = SparkSession.builder \
.master("local[1]") \
.appName("MySparkApp") \
.config("spark.some.config.option", "some-value") \
.getOrCreate()
```

[156]:
```
# Loading in the data frames for Alaska and Washington DC
```

[157]:
```
df_AK = spark.read\
.format("csv")\
.option("header", "true")\
.option("nullValue", "NA")\
.option("delimiter", "\t")\
.option("inferSchema", "true")\
.load('gs://final-proj-135/notebooks/jupyter/VM2Uniform--AK--2021-02-03.tab')
```

[158]:
```
df_DC = spark.read\
.format("csv")\
.option("header", "true")\
.option("nullValue", "NA")\
.option("delimiter", "\t")\
```

```
.option("inferSchema", "true")\
.load('gs://final-proj-135/notebooks/jupyter/VM2Uniform--DC--2021-01-30.tab')
```

[159]:
```
# importing packages
```

[160]:
```
from pyspark.sql.functions import *
import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml import Pipeline
from pyspark.ml.feature import RFormula, StringIndexer, OneHotEncoder, Imputer,␣
↪VectorAssembler, StandardScaler, Bucketizer
from pyspark.ml.classification import RandomForestClassifier,␣
↪DecisionTreeClassifier, LogisticRegression, NaiveBayes
from sklearn.metrics import classification_report, confusion_matrix
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder,␣
↪CrossValidatorModel
from pyspark.mllib.evaluation import MulticlassMetrics
from pyspark.sql.functions import regexp_replace, col
from pyspark.sql.types import LongType
```

0.1.3 Cleaning the Data

[161]:
```
# Taking a subset of the columns and updating the data frames
```

[162]:
```
df_AK = df_AK.select(['Voters_Gender', 'Voters_Age', 'Voters_BirthDate',␣
↪'Parties_Description', 'Ethnic_Description',\
'Religions_Description', 'MilitaryStatus_Description',␣
↪'MaritalStatus_Description', 'CommercialDataLL_Gun_Owner',\
'CommercialDataLL_Home_Owner_Or_Renter',␣
↪'CommercialDataLL_Interest_in_Electronic_Gaming_In_Household',␣
↪'PresidentialPrimary_2020',\
'Voters_VotingPerformanceEvenYearPrimary',␣
↪'CommercialDataLL_Interest_in_Shooting_In_Household'])
```

[163]:
```
df_DC = df_DC.select(['Voters_Gender', 'Voters_Age', 'Voters_BirthDate',␣
↪'Parties_Description', 'Ethnic_Description',\
'Religions_Description', 'MilitaryStatus_Description',␣
↪'MaritalStatus_Description', 'CommercialDataLL_Gun_Owner',\
```

```
'CommercialDataLL_Home_Owner_Or_Renter',␣
↪'CommercialDataLL_Interest_in_Electronic_Gaming_In_Household',␣
↪'PresidentialPrimary_2020',\
'Voters_VotingPerformanceEvenYearPrimary',␣
↪'CommercialDataLL_Interest_in_Shooting_In_Household'])
```

[164]:
```
# Caching our data frames
```

[165]:
```
df_AK = df_AK.cache()
```

23/03/22 23:27:40 WARN org.apache.spark.sql.execution.CacheManager: Asked to cache already cached data.

[166]:
```
df_DC = df_DC.cache()
```

23/03/22 23:27:40 WARN org.apache.spark.sql.execution.CacheManager: Asked to cache already cached data.

[167]:
```
# Renaming Columns
```

[168]:
```
df_AK = df_AK.withColumnRenamed("Voters_Gender", "Gender")\
       .withColumnRenamed("Voters_Age", "Age")\
       .withColumnRenamed("Voters_BirthDate", "Birthdate")\
       .withColumnRenamed("Parties_Description", "Party")\
       .withColumnRenamed("Ethnic_Description", "Ethnicity")\
       .withColumnRenamed("Religions_Description", "Religion")\
       .withColumnRenamed("MilitaryStatus_Description", "Military_Status")\
       .withColumnRenamed("MaritalStatus_Description", "Marital_Status")\
       .withColumnRenamed("CommercialDataLL_Gun_Owner", "Gun_Owner")\
       .withColumnRenamed("CommercialDataLL_Home_Owner_Or_Renter",␣
↪"Home_Owner_Or_Renter")\
       .
↪withColumnRenamed("CommercialDataLL_Interest_in_Electronic_Gaming_In_Household",␣
↪"EGame_Interest")\
       .withColumnRenamed("PresidentialPrimary_2020", "Primary2020")\
       .withColumnRenamed("Voters_VotingPerformanceEvenYearPrimary",␣
↪"Primary_Proportion_Voted")\
       .withColumnRenamed("CommercialDataLL_Interest_in_Shooting_In_Household",␣
↪"Interest_in_shooting")
```

[169]:
```
df_DC = df_DC.withColumnRenamed("Voters_Gender", "Gender")\
       .withColumnRenamed("Voters_Age", "Age")\
       .withColumnRenamed("Voters_BirthDate", "Birthdate")\
       .withColumnRenamed("Parties_Description", "Party")\
       .withColumnRenamed("Ethnic_Description", "Ethnicity")\
       .withColumnRenamed("Religions_Description", "Religion")\
       .withColumnRenamed("MilitaryStatus_Description", "Military_Status")\
```

```
        .withColumnRenamed("MaritalStatus_Description", "Marital_Status")\
        .withColumnRenamed("CommercialDataLL_Gun_Owner", "Gun_Owner")\
        .withColumnRenamed("CommercialDataLL_Home_Owner_Or_Renter",␣
↪"Home_Owner_Or_Renter")\
        .
↪withColumnRenamed("CommercialDataLL_Interest_in_Electronic_Gaming_In_Household",␣
↪"EGame_Interest")\
        .withColumnRenamed("PresidentialPrimary_2020", "Primary2020")\
        .withColumnRenamed("Voters_VotingPerformanceEvenYearPrimary",␣
↪"Primary_Proportion_Voted")\
        .withColumnRenamed("CommercialDataLL_Interest_in_Shooting_In_Household",␣
↪"Interest_in_shooting")
```

[170]:
```
# In the data frames, some column's null values were intended to be a "No". We␣
↪modify this below.
```

[171]:
```
df_AK = df_AK.na.fill(value = 'No', subset = 'Gun_Owner')
```

[172]:
```
df_DC = df_DC.na.fill(value = 'No', subset = 'Gun_Owner')
```

[173]:
```
df_AK = df_AK.na.fill(value = 'No', subset = 'EGame_Interest')
```

[174]:
```
df_DC = df_DC.na.fill(value = 'No', subset = 'EGame_Interest')
```

[175]:
```
df_AK = df_AK.na.fill(value = 'Not Married', subset = 'Marital_Status')
```

[176]:
```
df_DC = df_DC.na.fill(value = 'Not Married', subset = 'Marital_Status')
```

[177]:
```
df_AK = df_AK.na.fill(value = 'No', subset = 'Interest_in_shooting')
```

[178]:
```
df_DC = df_DC.na.fill(value = 'No', subset = 'Interest_in_shooting')
```

[179]:
```
# Counting the number of rows
```

[180]:
```
df_AK.count()
```

[180]: 548259

[181]:
```
df_DC.count()
```

[181]: 473913

[182]:
```
# Counting missing values in each column after modifying columns
```

[183]:
```
df_AK.select(*(sum(col(c).isNull().cast("int")).alias(c) for c in df_AK.
↪columns)).collect()
```

[183]: [Row(Gender=66, Age=215368, Birthdate=215368, Party=0, Ethnicity=71026, Religion=388240, Military_Status=548259, Marital_Status=0, Gun_Owner=0, Home_Owner_Or_Renter=198182, EGame_Interest=0, Primary2020=548259, Primary_Proportion_Voted=0, Interest_in_shooting=0)]

[184]:
```
df_DC.select(*(sum(col(c).isNull().cast("int")).alias(c) for c in df_DC.
↪columns)).collect()
```

[184]: [Row(Gender=19601, Age=193536, Birthdate=193536, Party=0, Ethnicity=37325, Religion=329504, Military_Status=473913, Marital_Status=0, Gun_Owner=0, Home_Owner_Or_Renter=71185, EGame_Interest=0, Primary2020=365971, Primary_Proportion_Voted=0, Interest_in_shooting=0)]

df_AK has 548,259 rows and 12 columns and df_DC has 473,913 rows and 12 columns. The schemas are shown below.

[185]:
```
df_AK.printSchema()
```

```
root
 |-- Gender: string (nullable = true)
 |-- Age: integer (nullable = true)
 |-- Birthdate: string (nullable = true)
 |-- Party: string (nullable = true)
 |-- Ethnicity: string (nullable = true)
 |-- Religion: string (nullable = true)
 |-- Military_Status: string (nullable = true)
 |-- Marital_Status: string (nullable = false)
 |-- Gun_Owner: string (nullable = false)
 |-- Home_Owner_Or_Renter: string (nullable = true)
 |-- EGame_Interest: string (nullable = false)
 |-- Primary2020: string (nullable = true)
 |-- Primary_Proportion_Voted: string (nullable = true)
 |-- Interest_in_shooting: string (nullable = false)
```

[186]:
```
df_DC.printSchema()
```

```
root
 |-- Gender: string (nullable = true)
 |-- Age: integer (nullable = true)
 |-- Birthdate: string (nullable = true)
 |-- Party: string (nullable = true)
 |-- Ethnicity: string (nullable = true)
 |-- Religion: string (nullable = true)
 |-- Military_Status: string (nullable = true)
 |-- Marital_Status: string (nullable = false)
 |-- Gun_Owner: string (nullable = false)
 |-- Home_Owner_Or_Renter: string (nullable = true)
```

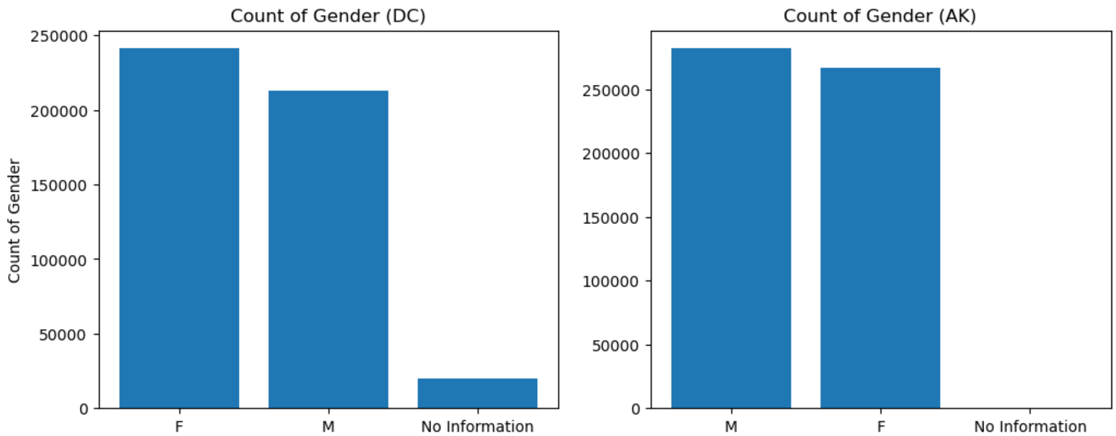
```
 |-- EGame_Interest: string (nullable = false)
 |-- Primary2020: string (nullable = true)
 |-- Primary_Proportion_Voted: string (nullable = true)
 |-- Interest_in_shooting: string (nullable = false)
```

0.1.4 Exploratory Data Analysis

We will first explore the gender, age, ethnicity, religion, and party data in DC and Alaska.

[187]:
```
df_DC_new = df_DC
df_AK_new = df_AK

DC_Gender = df_DC_new.select('Gender', 'Party').groupby(df_DC_new.Gender).
 ↪count().sort('count', ascending=False)
DC_Gender = DC_Gender.toPandas()
DC_Gender.fillna("No Information",inplace=True)

AK_Gender = df_AK_new.select('Gender', 'Party').groupby(df_AK_new.Gender).
 ↪count().sort('count', ascending=False)
AK_Gender = AK_Gender.toPandas()
AK_Gender.fillna("No Information",inplace=True)
```

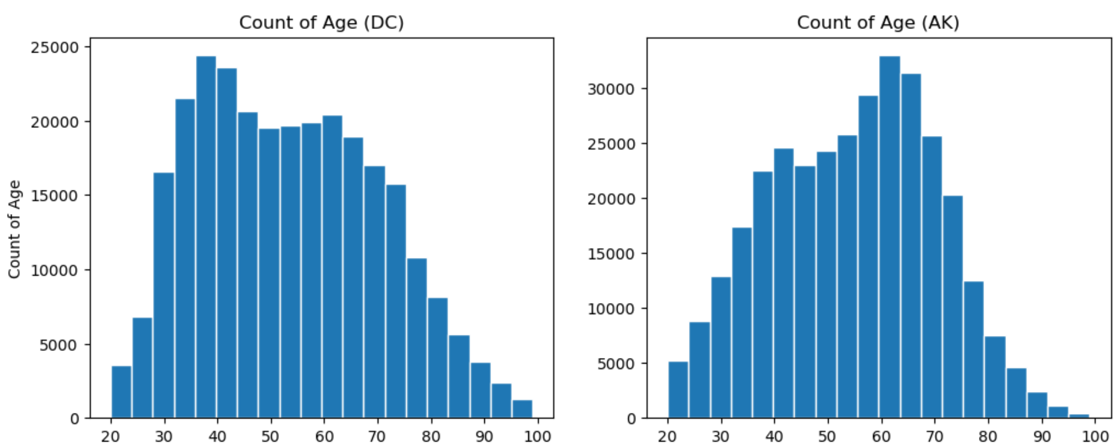
[188]:
```
fig, ax = plt.subplots(1, 2)
fig.set_size_inches(12, 4.5)
ax[0].bar(DC_Gender['Gender'], DC_Gender['count'])
ax[0].set_ylabel('Count of Gender')
ax[0].set_title('Count of Gender (DC)')
ax[1].bar(AK_Gender['Gender'], AK_Gender['count'])
ax[1].set_title('Count of Gender (AK)')
plt.show()
```



We can see that there are more female registered voters in DC, while there are more male registered voters in Alaska. There are around 25000 unknown gender voters in DC, while the gender of most of the voters in Alaska are known.

[189]:
```
DC_Age = df_DC_new.select('Age').toPandas()
DC_Age.fillna("",inplace=True)
DC_Age['Age'] = pd.to_numeric(DC_Age['Age'])

AK_Age = df_AK_new.select('Age').toPandas()
AK_Age.fillna("",inplace=True)
AK_Age['Age'] = pd.to_numeric(AK_Age['Age'])
```

[190]:
```
fig, ax = plt.subplots(1, 2)
fig.set_size_inches(12, 4.5)
ax[0].hist(x=DC_Age['Age'], bins=20, edgecolor="white")
ax[0].set_ylabel('Count of Age')
ax[0].set_title('Count of Age (DC)')
ax[1].hist(x=AK_Age['Age'], bins=20, edgecolor="white")
ax[1].set_title('Count of Age (AK)')
plt.show()
```



The voters in DC seem to generally younger than the voters in Alaska. The voters' age in DC concentrate between 30 and 50 years old, while the voters' age in Alaska concentrate between 50 and 70 years old.

[191]:
```
DC_Ethnicity = df_DC_new.select('Ethnicity', 'Party').groupby(df_DC_new.
 ↪Ethnicity).count().sort("count", ascending=False)
DC_Ethnicity = DC_Ethnicity.toPandas()
DC_Ethnicity.fillna("No Information",inplace=True)

AK_Ethnicity = df_AK_new.select('Ethnicity', 'Party').groupby(df_AK_new.
 ↪Ethnicity).count().sort("count", ascending=False)
AK_Ethnicity = AK_Ethnicity.toPandas()
```

```
AK_Ethnicity.fillna("No Information",inplace=True)
```

[192]:
```
E = [['DC Ethnicity', DC_Ethnicity['Ethnicity'].count()-1], ['AK Ethnicity',␣
 ↪AK_Ethnicity['Ethnicity'].count()-1]]
pd.DataFrame(E)
```

[192]:
```
              0   1
0  DC Ethnicity  81
1  AK Ethnicity  77
```

There are 81 known different ethnicities among the voters in DC, and there are 77 known different ethnicities among the voters in Alaska. We will show the top 15 largest ethnicities in DC and Alaska.

[193]:
```
Ethnicity = pd.concat([DC_Ethnicity[:15],AK_Ethnicity[:15]],axis=1,join='outer')
Ethnicity.columns = ['Ethnicity (DC)', 'count (DC)', 'Ethnicity (AK)', 'count␣
 ↪(AK)']
Ethnicity
```

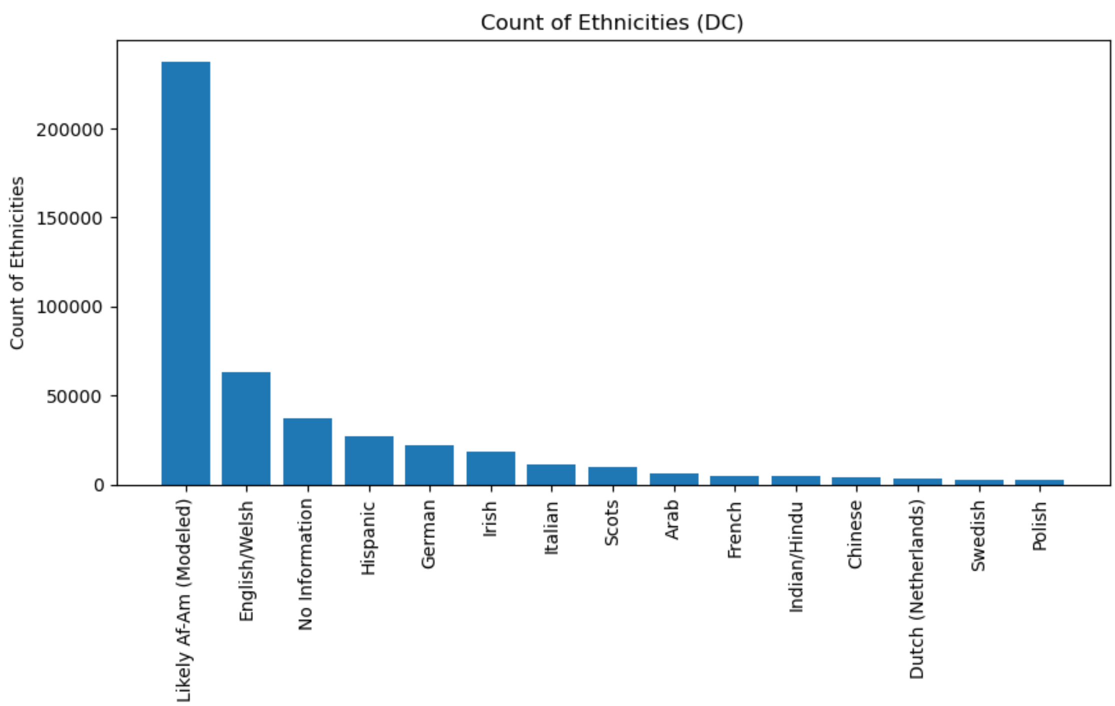
[193]:
```
               Ethnicity (DC)  count (DC)  \
0   Likely Af-Am (Modeled)      237598
1            English/Welsh       62936
2           No Information       37325
3                 Hispanic       27268
4                   German       22272
5                    Irish       18878
6                  Italian       11621
7                    Scots        9562
8                     Arab        6054
9                   French        5131
10            Indian/Hindu        4638
11                 Chinese        4229
12     Dutch (Netherlands)        3637
13                 Swedish        2900
14                  Polish        2886

                             Ethnicity (AK)  count (AK)
0                             English/Welsh      225110
1                            No Information       71026
2                                    German       43022
3                                     Irish       37277
4                                     Scots       34721
5                                  Hispanic       31260
6                                    French       13850
7                                   Swedish       12833
8                                   Italian       10471
9                       Dutch (Netherlands)       10178
```

```
10                                  Norwegian        6177
11  Russian (omitting former Soviet States)        4928
12                                     Polish        4875
13                       Likely Af-Am (Modeled)        4784
14                                    Chinese        4697
```

The ethnicity with the largest population in DC is Likely Af-Am (Modeled), and the second largest ethnicity is English/Welsh. The ethnicity with the largest population in Alaska is English/Welsh, and the second largest ethnicity is German (we ignore the unknown ethnicities here).

[194]:

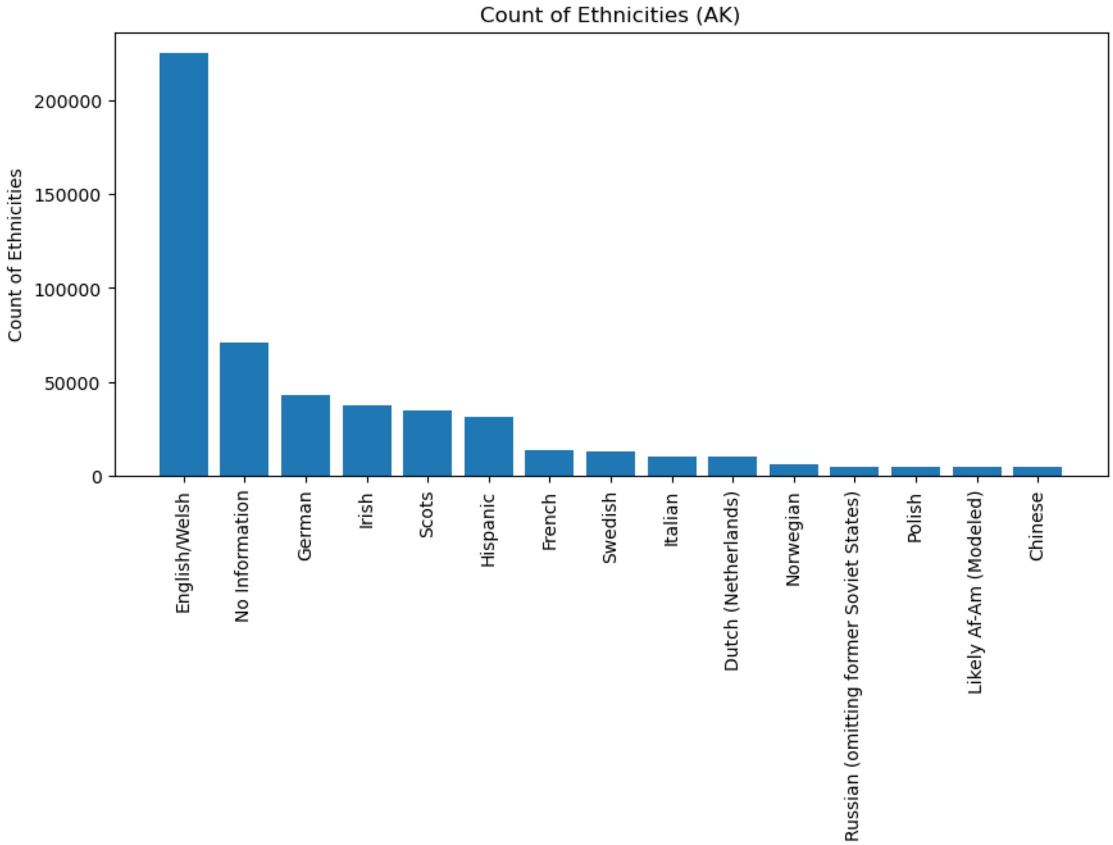
```
fig, ax = plt.subplots()
fig.set_size_inches(10, 4.5)
ax.bar(DC_Ethnicity['Ethnicity'].iloc[:15], DC_Ethnicity['count'].iloc[:15])
ax.set_xticklabels(DC_Ethnicity['Ethnicity'], rotation=90)
ax.set_ylabel('Count of Ethnicities')
ax.set_title('Count of Ethnicities (DC)')
plt.show()
```



[195]:

```
fig, ax = plt.subplots()
fig.set_size_inches(10, 4.5)
ax.bar(AK_Ethnicity['Ethnicity'].iloc[:15], AK_Ethnicity['count'].iloc[:15])
ax.set_xticklabels(AK_Ethnicity['Ethnicity'], rotation=90)
ax.set_ylabel('Count of Ethnicities')
ax.set_title('Count of Ethnicities (AK)')
```

```
plt.show()
```



[196]:
```
DC_Religion = df_DC_new.select('Religion', 'Party').groupby(df_DC_new.Religion).
 ↪count().sort("count", ascending=False)
DC_Religion = DC_Religion.toPandas()
DC_Religion.fillna("No Information",inplace=True)

AK_Religion = df_AK_new.select('Religion', 'Party').groupby(df_AK_new.Religion).
 ↪count().sort("count", ascending=False)
AK_Religion = AK_Religion.toPandas()
AK_Religion.fillna("No Information",inplace=True)
```

[197]:
```
R = [['DC Religion', DC_Religion['Religion'].count()-1], ['AK Religion',␣
 ↪AK_Religion['Religion'].count()-1]]
pd.DataFrame(R)
```

[197]:

	0	1
0	DC Religion	13
1	AK Religion	13

We can see that there are 13 known religions among the voters in both DC and Alaska.

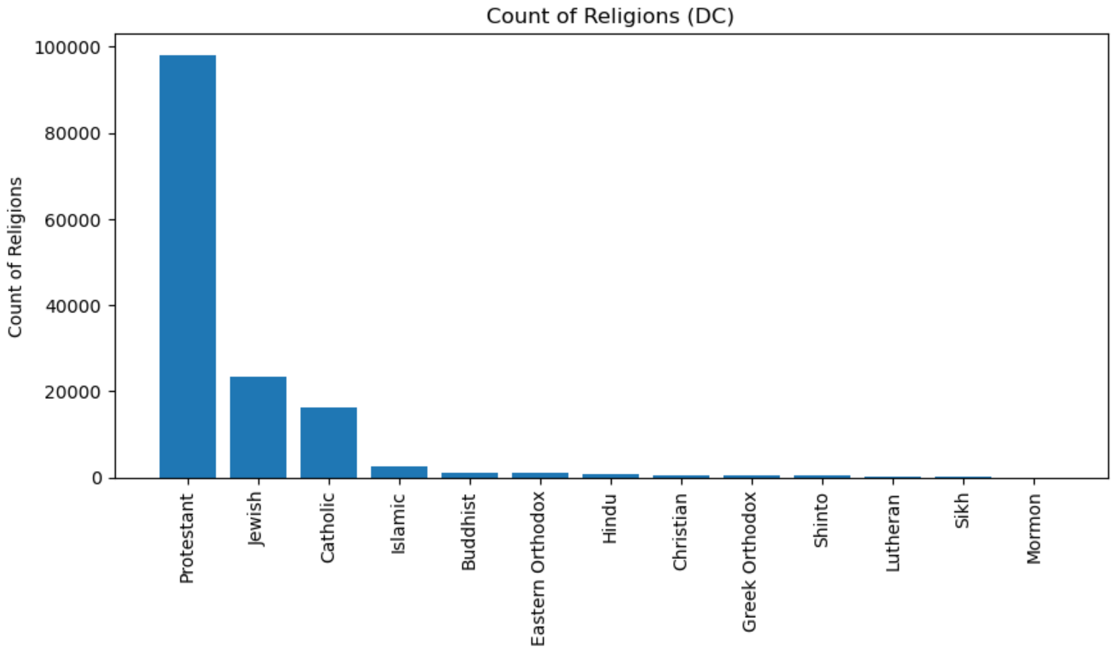
[198]:
```
Religion = pd.concat([DC_Religion,AK_Religion],axis=1,join='outer')
Religion.columns = ['Religion (DC)', 'count (DC)', 'Religion (AK)', 'count␣
↪(AK)']
Religion
```

[198]:

	Religion (DC)	count (DC)	Religion (AK)	count (AK)
0	No Information	329504	No Information	388240
1	Protestant	98184	Protestant	101995
2	Jewish	23266	Catholic	31117
3	Catholic	16190	Jewish	19677
4	Islamic	2641	Eastern Orthodox	2184
5	Buddhist	1087	Christian	1614
6	Eastern Orthodox	944	Buddhist	1570
7	Hindu	856	Shinto	606
8	Christian	440	Islamic	443
9	Greek Orthodox	386	Greek Orthodox	338
10	Shinto	314	Lutheran	236
11	Lutheran	72	Hindu	188
12	Sikh	27	Mormon	45
13	Mormon	2	Sikh	6

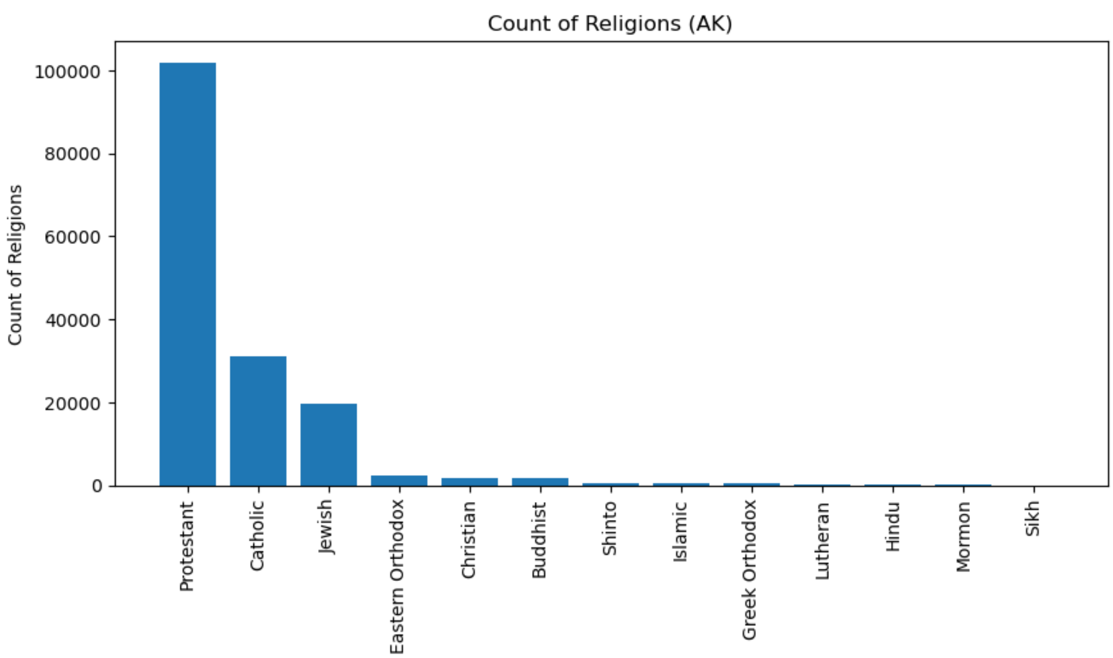
Most of the voters do not have the information of their religions. In both DC and Alaska, the known religion with the largest population is Protestant. In DC, the second largest religion is Jewish, and the third largest religion is Catholic. In Alaska, the second largest religion is Catholic, and the third largest religion is Jewish.

[199]:
```
fig, ax = plt.subplots()
fig.set_size_inches(10, 4.5)
ax.bar(DC_Religion['Religion'][1:], DC_Religion['count'][1:])
ax.set_xticklabels(DC_Religion['Religion'][1:], rotation=90)
ax.set_ylabel('Count of Religions')
ax.set_title('Count of Religions (DC)')
plt.show()
```



[200]:

```
fig, ax = plt.subplots()
fig.set_size_inches(10, 4.5)
ax.bar(AK_Religion['Religion'][1:], AK_Religion['count'][1:])
ax.set_xticklabels(AK_Religion['Religion'][1:], rotation=90)
ax.set_ylabel('Count of Religions')
ax.set_title('Count of Religions (AK)')
plt.show()
```



[201]:
```
DC_Parties = df_DC_new.select('Party', 'Party').groupby(df_DC_new.Party).
 ↪count().sort("count", ascending=False)
DC_Parties = DC_Parties.toPandas()
DC_Parties.fillna("No Information",inplace=True)

AK_Parties = df_AK_new.select('Party', 'Party').groupby(df_AK_new.Party).
 ↪count().sort("count", ascending=False)
AK_Parties = AK_Parties.toPandas()
AK_Parties.fillna("No Information",inplace=True)
```

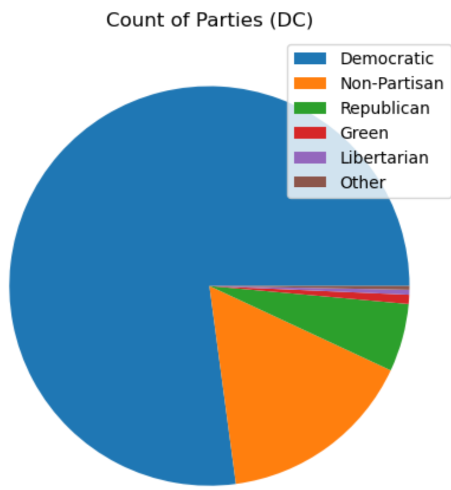
[202]:
```
Party = pd.concat([DC_Parties,AK_Parties],axis=1,join='outer')
Party.columns = ['Party (DC)', 'count (DC)', 'Party (AK)', 'count (AK)']
Party
```

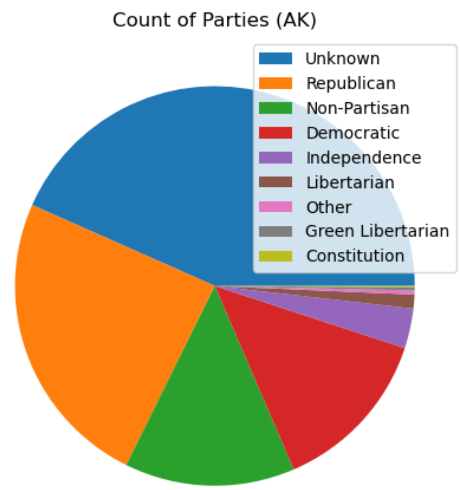
[202]:

	Party (DC)	count (DC)	Party (AK)	count (AK)
0	Democratic	365463.0	Unknown	237742
1	Non-Partisan	75549.0	Republican	133370
2	Republican	26063.0	Non-Partisan	75520
3	Green	3506.0	Democratic	73994
4	Libertarian	1884.0	Independence	17667
5	Other	1448.0	Libertarian	6202
6	NaN	NaN	Other	1765
7	NaN	NaN	Green Libertarian	1406
8	NaN	NaN	Constitution	593

In DC, most voters registered for Democratic. In Alaska, most voters registered for Unknown parties. The known party with the most voters in Alaska is Republican.

[203]:
```
fig, ax = plt.subplots(1, 2)
fig.set_size_inches(12, 5.5)
ax[0].pie(DC_Parties['count'])
ax[0].set_title('Count of Parties (DC)')
ax[0].legend(DC_Parties['Party'])
ax[1].pie(AK_Parties['count'])
ax[1].set_title('Count of Parties (AK)')
ax[1].legend(AK_Parties['Party'])
plt.show()
```

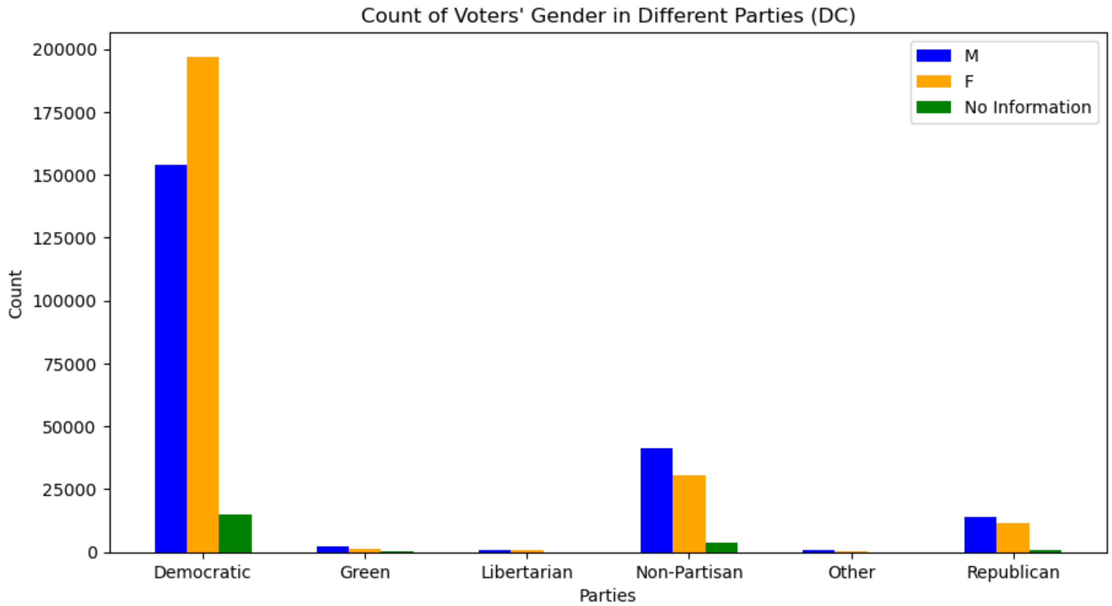




We will then start to explore how gender, ethnicity, and religion will influence the voters' parties preference.

[204]:
```
DC_P_G = df_DC_new.groupby(['Party', 'Gender']).count().sort(['Party',␣
↪'Gender'], ascending=[True, False])
DC_P_G = DC_P_G.toPandas()
DC_P_G.fillna("No Information",inplace=True)
```

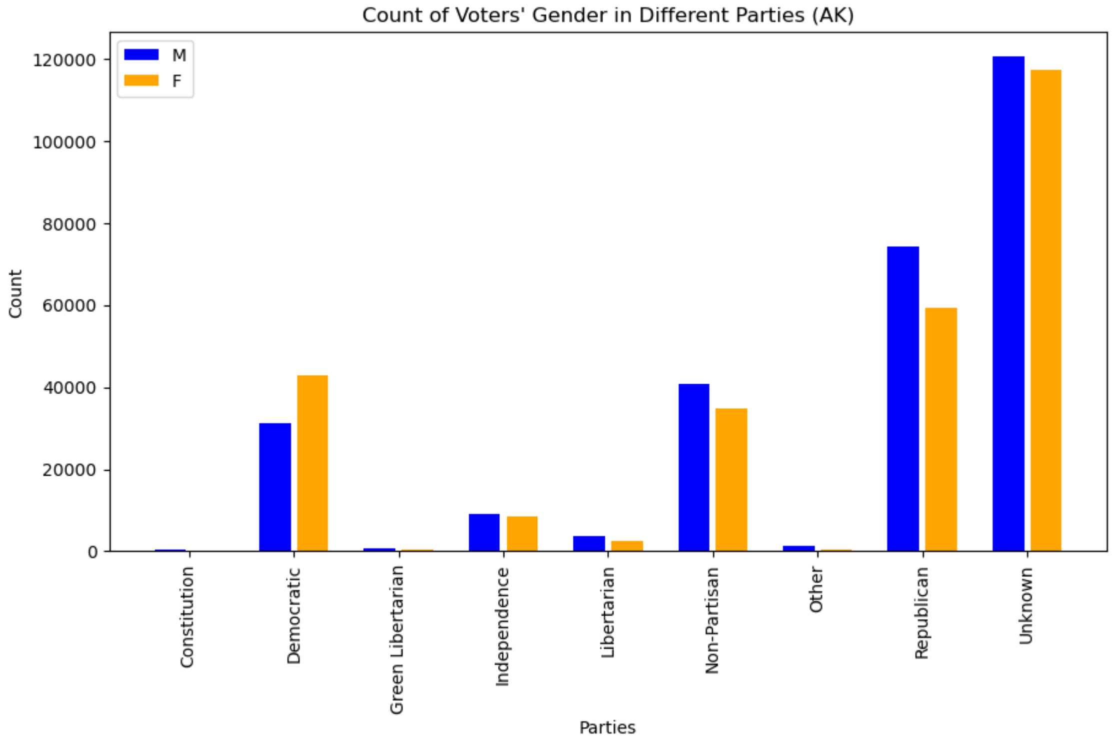
[205]:
```
x = np.arange(6)
width = 0.2

fig, ax = plt.subplots()
fig.set_size_inches(10.5, 5.5)
ax.bar(x-0.2, np.array(DC_P_G[DC_P_G.Gender=='M']['count']), width,␣
↪color='blue')
ax.bar(x, np.array(DC_P_G[DC_P_G.Gender=='F']['count']), width, color='orange')
ax.bar(x+0.2, np.array(DC_P_G[DC_P_G.Gender=='No Information']['count']),␣
↪width, color='green')
ax.set_title("Count of Voters' Gender in Different Parties (DC)")
plt.xticks(x, np.array(DC_P_G['Party'].unique()))
plt.xlabel("Parties")
plt.ylabel("Count")
plt.legend(["M", "F", "No Information"])
plt.show()
```



In DC, more female voters support Democratic than male voters, while more male voters support Non-Partisan and Republican than female voters.

[206]:
```
AK_P_G = df_AK_new.groupby(['Party', 'Gender']).count().sort(['Party',␣
↪'Gender'], ascending=[True, False])
AK_P_G = AK_P_G.toPandas()
AK_P_G.fillna("No Information",inplace=True)
```

[207]:
```
x = np.arange(9)
width = 0.3

fig, ax = plt.subplots()
fig.set_size_inches(10.5, 5.5)
ax.bar(x-0.18, np.array(AK_P_G[AK_P_G.Gender=='M']['count']), width,␣
↪color='blue')
ax.bar(x+0.18, np.array(AK_P_G[AK_P_G.Gender=='F']['count']), width,␣
↪color='orange')
ax.set_title("Count of Voters' Gender in Different Parties (AK)")
plt.xticks(x, np.array(AK_P_G['Party'].unique()), rotation=90)
plt.xlabel("Parties")
plt.ylabel("Count")
plt.legend(["M", "F", "No Information"])
plt.show()
```

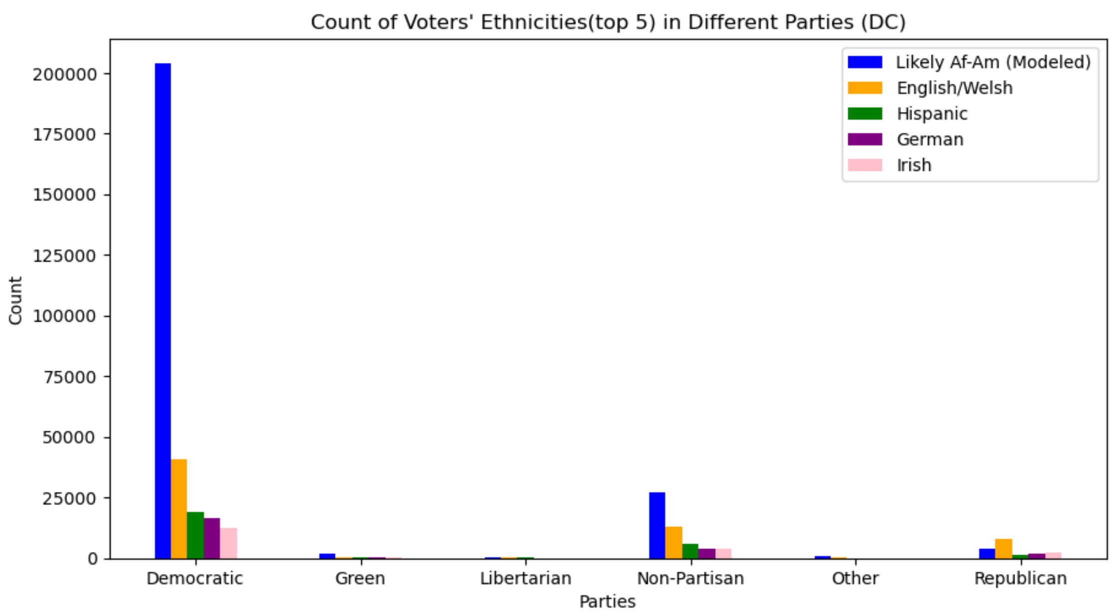


In Alaska, more male voters registered for unknown party than female voters. More male voters support Non-Partisan and Republican than female voters, while more female voters support Democratic than male voters. From the data of these states, it seems like female voters are more likely to support Democratic than male voters.

[208]:
```
DC_tmp = df_DC_new.filter((df_DC_new.Ethnicity == 'Likely Af-Am (Modeled)') | \
                          (df_DC_new.Ethnicity == 'English/Welsh') | \
                          (df_DC_new.Ethnicity == 'Hispanic') | \
                          (df_DC_new.Ethnicity == 'German') | \
                          (df_DC_new.Ethnicity == 'Irish'))
DC_P_E = DC_tmp.groupby(['Party', 'Ethnicity']).count().sort(['Party',␣
 ↪'Ethnicity'])
DC_P_E = DC_P_E.toPandas()
```

[209]:
```
x = np.arange(6)
width = 0.1

fig, ax = plt.subplots()
fig.set_size_inches(10.5, 5.5)
ax.bar(x-0.2, np.array(DC_P_E[DC_P_E.Ethnicity=='Likely Af-Am␣
 ↪(Modeled)']['count']), width, color='blue')
ax.bar(x-0.1, np.array(DC_P_E[DC_P_E.Ethnicity=='English/Welsh']['count']),␣
 ↪width, color='orange')
```

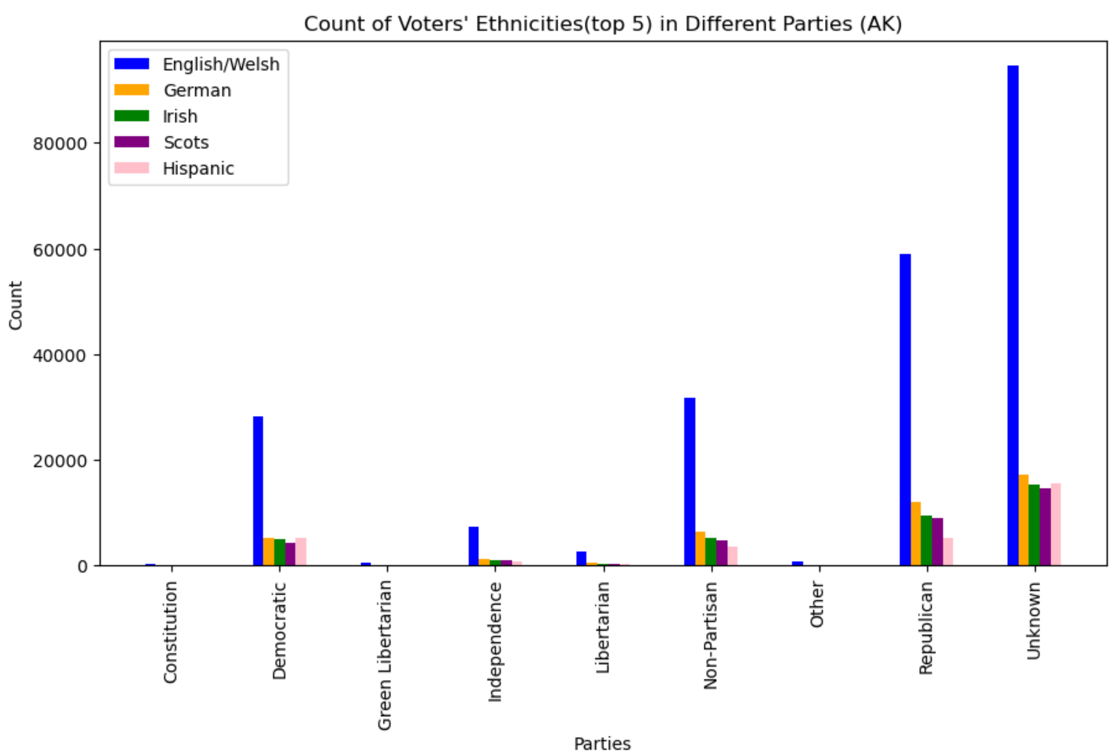
```
ax.bar(x, np.array(DC_P_E[DC_P_E.Ethnicity=='Hispanic']['count']), width,␣
↪color='green')
ax.bar(x+0.1, np.array(DC_P_E[DC_P_E.Ethnicity=='German']['count']), width,␣
↪color='purple')
ax.bar(x+0.2, np.array(DC_P_E[DC_P_E.Ethnicity=='Irish']['count']), width,␣
↪color='pink')
ax.set_title("Count of Voters' Ethnicities(top 5) in Different Parties (DC)")
plt.xticks(x, np.array(DC_P_E['Party'].unique()))
plt.xlabel("Parties")
plt.ylabel("Count")
plt.legend(['Likely Af-Am (Modeled)','English/
↪Welsh','Hispanic','German','Irish'])
plt.show()
```



Generally, the ethnicity with larger population has more registered voters in each party. However, in DC, there are more English/Welsh voters support Republican, while Likely Af-Am (Modeled) has larger population.

[210]:
```
AK_tmp = df_AK_new.filter((df_AK_new.Ethnicity == 'English/Welsh') | \
                          (df_AK_new.Ethnicity == 'German') | \
                          (df_AK_new.Ethnicity == 'Irish') | \
                          (df_AK_new.Ethnicity == 'Scots') | \
                          (df_AK_new.Ethnicity == 'Hispanic'))
AK_P_E = AK_tmp.groupby(['Party', 'Ethnicity']).count().sort(['Party',␣
↪'Ethnicity'])
AK_P_E = AK_P_E.toPandas()
```

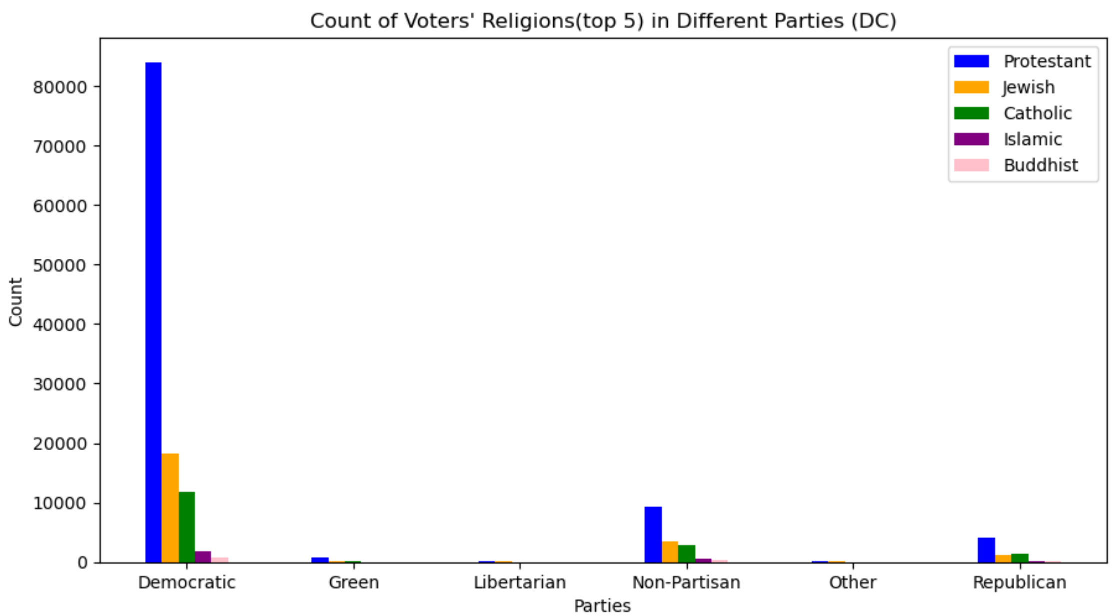
[211]:
```
x = np.arange(9)
width = 0.1

fig, ax = plt.subplots()
fig.set_size_inches(10.5, 5.5)
ax.bar(x-0.2, np.array(AK_P_E[AK_P_E.Ethnicity=='English/Welsh']['count']),␣
 ↪width, color='blue')
ax.bar(x-0.1, np.array(AK_P_E[AK_P_E.Ethnicity=='German']['count']), width,␣
 ↪color='orange')
ax.bar(x, np.array(AK_P_E[AK_P_E.Ethnicity=='Irish']['count']), width,␣
 ↪color='green')
ax.bar(x+0.1, np.array(AK_P_E[AK_P_E.Ethnicity=='Scots']['count']), width,␣
 ↪color='purple')
ax.bar(x+0.2, np.array(AK_P_E[AK_P_E.Ethnicity=='Hispanic']['count']), width,␣
 ↪color='pink')
ax.set_title("Count of Voters' Ethnicities(top 5) in Different Parties (AK)")
plt.xticks(x, np.array(AK_P_E['Party'].unique()), rotation=90)
plt.xlabel("Parties")
plt.ylabel("Count")
plt.legend(['English/Welsh','German','Irish','Scots','Hispanic'])
plt.show()
```



In Alaska, Hispanic voters are more likely to support Democratic and unknown parties. There are less Hispanic voters support Republican.

[212]:
```
DC_tmp = df_DC_new.filter((df_DC_new.Religion == 'Protestant') | \
                          (df_DC_new.Religion == 'Jewish') | \
                          (df_DC_new.Religion == 'Catholic') | \
                          (df_DC_new.Religion == 'Islamic') | \
                          (df_DC_new.Religion == 'Buddhist'))
DC_P_R = DC_tmp.groupby(['Party', 'Religion']).count().sort(['Party',␣
 ↪'Religion'])
DC_P_R = DC_P_R.toPandas()
```

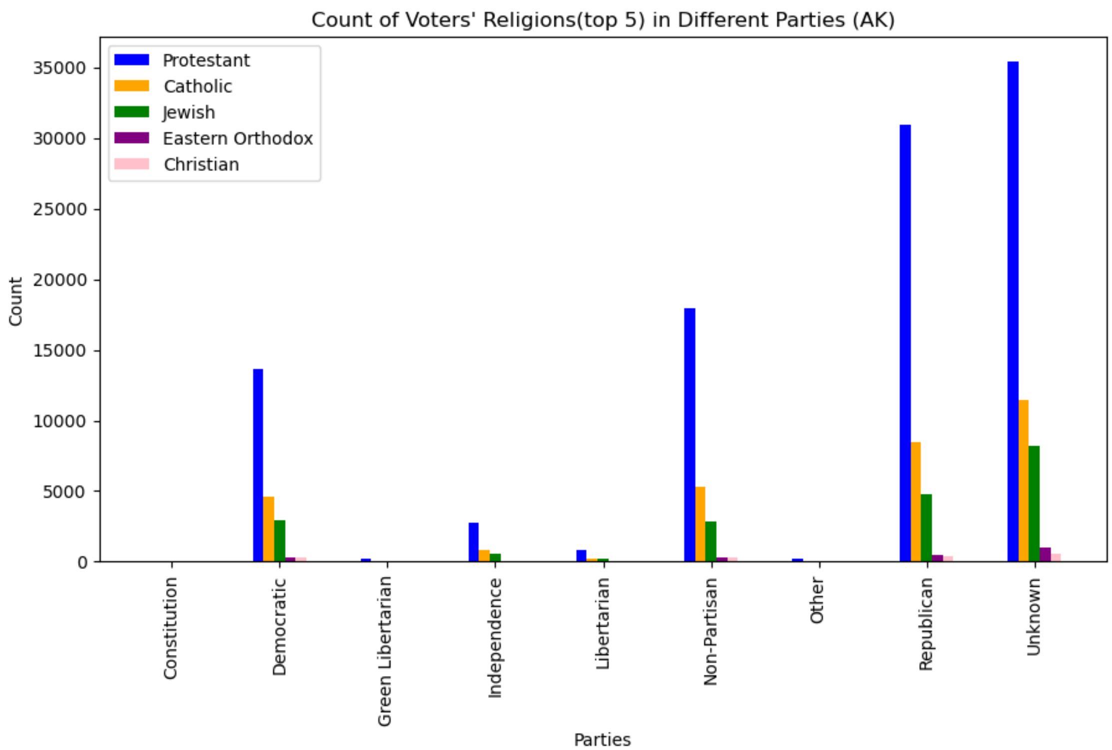
[213]:
```
x = np.arange(6)
width = 0.1

fig, ax = plt.subplots()
fig.set_size_inches(10.5, 5.5)
ax.bar(x-0.2, np.array(DC_P_R[DC_P_R.Religion=='Protestant']['count']), width,␣
 ↪color='blue')
ax.bar(x-0.1, np.array(DC_P_R[DC_P_R.Religion=='Jewish']['count']), width,␣
 ↪color='orange')
ax.bar(x, np.array(DC_P_R[DC_P_R.Religion=='Catholic']['count']), width,␣
 ↪color='green')
ax.bar(x+0.1, np.array(DC_P_R[DC_P_R.Religion=='Islamic']['count']), width,␣
 ↪color='purple')
ax.bar(x+0.2, np.array(DC_P_R[DC_P_R.Religion=='Buddhist']['count']), width,␣
 ↪color='pink')
ax.set_title("Count of Voters' Religions(top 5) in Different Parties (DC)")
plt.xticks(x, np.array(DC_P_R['Party'].unique()))
plt.xlabel("Parties")
plt.ylabel("Count")
plt.legend(['Protestant','Jewish','Catholic','Islamic','Buddhist'])
plt.show()
```



[214]:
```
AK_tmp = df_AK_new.filter((df_AK_new.Religion == 'Protestant') | \
                          (df_AK_new.Religion == 'Catholic') | \
                          (df_AK_new.Religion == 'Jewish') | \
                          (df_AK_new.Religion == 'Eastern Orthodox') | \
                          (df_AK_new.Religion == 'Christian'))
AK_P_R = AK_tmp.groupby(['Party', 'Religion']).count().sort(['Party',␣
↪'Religion'])
AK_P_R = AK_P_R.toPandas()
```

[215]:
```
x = np.arange(9)
width = 0.1

fig, ax = plt.subplots()
fig.set_size_inches(10.5, 5.5)
ax.bar(x-0.2, np.array(AK_P_R[AK_P_R.Religion=='Protestant']['count']), width,␣
↪color='blue')
ax.bar(x-0.1, np.array(AK_P_R[AK_P_R.Religion=='Catholic']['count']), width,␣
↪color='orange')
ax.bar(x, np.array(AK_P_R[AK_P_R.Religion=='Jewish']['count']), width,␣
↪color='green')
ax.bar(x+0.1, np.array(AK_P_R[AK_P_R.Religion=='Eastern Orthodox']['count']),␣
↪width, color='purple')
ax.bar(x+0.2, np.array(AK_P_R[AK_P_R.Religion=='Christian']['count']), width,␣
↪color='pink')
ax.set_title("Count of Voters' Religions(top 5) in Different Parties (AK)")
plt.xticks(x, np.array(AK_P_R['Party'].unique()), rotation=90)
```

```
plt.xlabel("Parties")
plt.ylabel("Count")
plt.legend(['Protestant','Catholic','Jewish','Eastern Orthodox','Christian'])
plt.show()
```

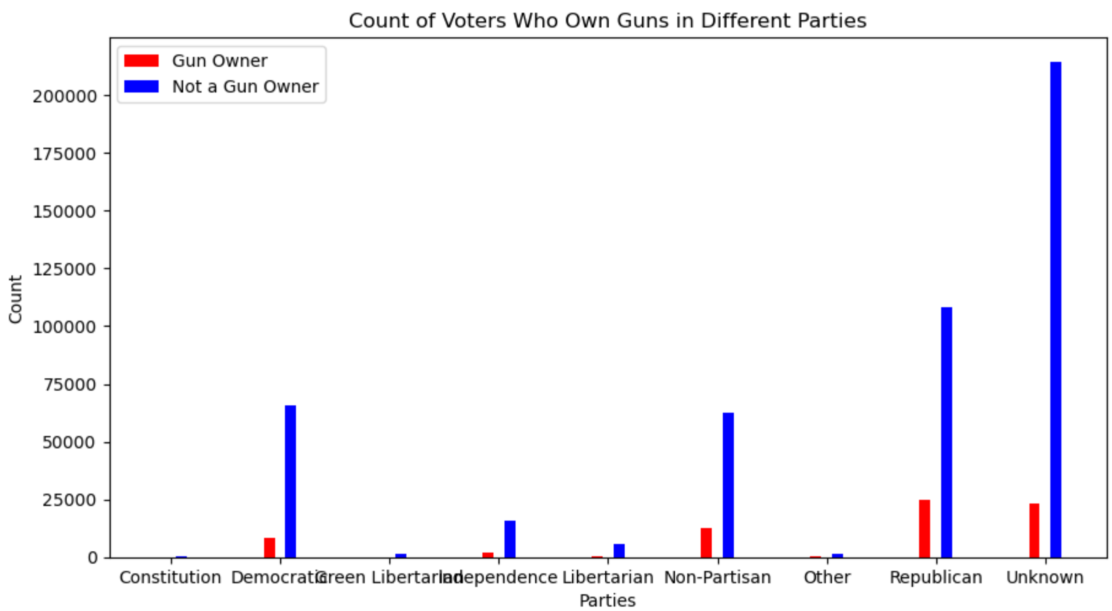


Generally, the religion with larger population has more registered voters in each party in both DC and Alaska.

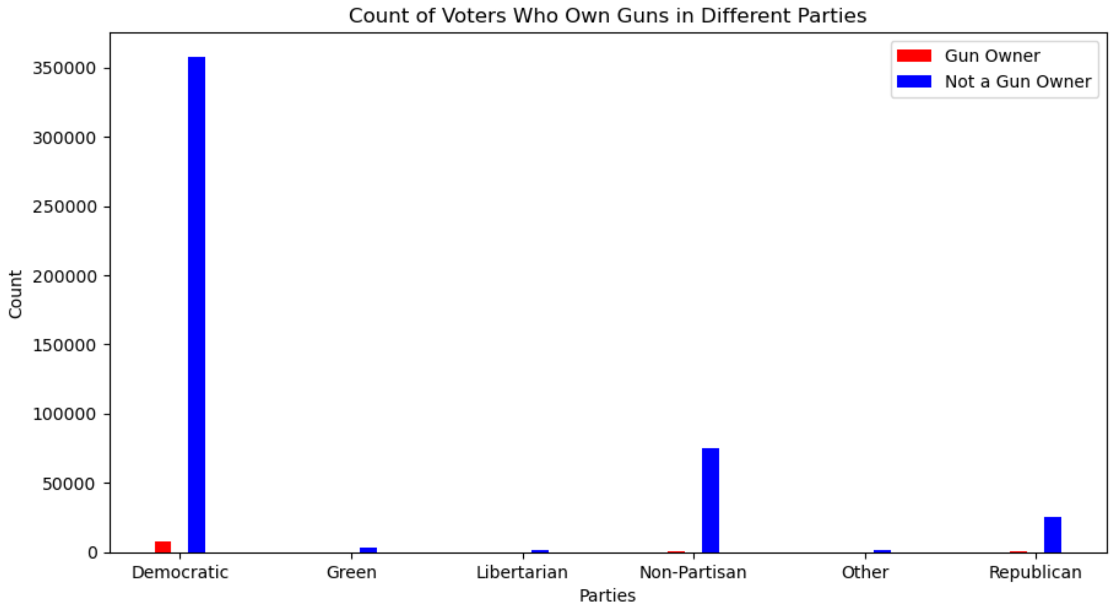
[216]:
```
df_AK_copy = df_AK.groupby(['Party', 'Gun_Owner']).count().sort(['Party',␣
↪'Gun_Owner'])
df_AK_copy = df_AK_copy.toPandas()
df_DC_copy = df_DC.groupby(['Party', 'Gun_Owner']).count().sort(['Party',␣
↪'Gun_Owner'])
df_DC_copy = df_DC_copy.toPandas()
```

[217]:
```
x = np.arange(9)
width = 0.1

fig, ax = plt.subplots()
fig.set_size_inches(10.5, 5.5)
ax.bar(x-0.1, np.array(df_AK_copy[df_AK_copy['Gun_Owner']=='Yes']['count']),␣
↪width, color='red')
```

```
ax.bar(x+0.1, np.array(df_AK_copy[df_AK_copy['Gun_Owner']=='No']['count']),␣
↪width, color='blue')
ax.set_title("Count of Voters Who Own Guns in Different Parties")
plt.xticks(x, np.array(df_AK_copy['Party'].unique()))
plt.xlabel("Parties")
plt.ylabel("Count")
plt.legend(['Gun Owner', 'Not a Gun Owner'])
plt.show()
```



[218]:
```
x = np.arange(6)
width = 0.1

fig, ax = plt.subplots()
fig.set_size_inches(10.5, 5.5)
ax.bar(x-0.1, np.array(df_DC_copy[df_DC_copy['Gun_Owner']=='Yes']['count']),␣
↪width, color='red')
ax.bar(x+0.1, np.array(df_DC_copy[df_DC_copy['Gun_Owner']=='No']['count']),␣
↪width, color='blue')
ax.set_title("Count of Voters Who Own Guns in Different Parties")
plt.xticks(x, np.array(df_DC_copy['Party'].unique()))
plt.xlabel("Parties")
plt.ylabel("Count")
plt.legend(['Gun Owner', 'Not a Gun Owner'])
plt.show()
```



We first notice when comparing gun ownership in Alaska and DC that DC does not have voters registered for the Constitution, Independent, or Unknown party. We also notice that there is a vastly larger count of Democrats in DC than Alaska. Across states, there are more people that are not gun owners. Finally, Alaska has a higher count of gun owners than DC across parties.

0.1.5 Gamers && Shooting

1) Making a graph on the correlation between being a gamer and party affiliation
2) Making a graph on the correlation between being a shooting enthusiast and party affiliation

[219]:
```
ak = df_AK.select(['Birthdate', 'Party', 'Gun_Owner',
                   'EGame_Interest', 'Interest_in_shooting',
                   'Primary_Proportion_Voted'])

dc = df_DC.select(['Birthdate', 'Party', 'Gun_Owner',
                   'EGame_Interest', 'Interest_in_shooting',
                   'Primary_Proportion_Voted'])
```

[220]:
```
ak.count()
```

[220]: 548259

[221]:
```
dc.count()
```

[221]: 473913

[222]:
```
ak.printSchema()
```

```
root
 |-- Birthdate: string (nullable = true)
 |-- Party: string (nullable = true)
 |-- Gun_Owner: string (nullable = false)
 |-- EGame_Interest: string (nullable = false)
 |-- Interest_in_shooting: string (nullable = false)
 |-- Primary_Proportion_Voted: string (nullable = true)
```

[223]:
```
dc.printSchema()
```

```
root
 |-- Birthdate: string (nullable = true)
 |-- Party: string (nullable = true)
 |-- Gun_Owner: string (nullable = false)
 |-- EGame_Interest: string (nullable = false)
 |-- Interest_in_shooting: string (nullable = false)
 |-- Primary_Proportion_Voted: string (nullable = true)
```

[224]:
```
ak = ak.cache()
dc = dc.cache()
```

```
23/03/22 23:27:59 WARN org.apache.spark.sql.execution.CacheManager: Asked to
cache already cached data.
23/03/22 23:27:59 WARN org.apache.spark.sql.execution.CacheManager: Asked to
cache already cached data.
```

[225]:
```
alaskans_gamers = ak.filter(ak.EGame_Interest == "Yes")\
.groupby("Party").count().sort('count', ascending=False)


alaskans_shooting = ak.filter(ak.Interest_in_shooting == "Yes")\
.groupby("Party").count().sort('count', ascending=False)
```

[226]:
```
alaskans_gamers.show()
```

```
+-----------------+-----+
|            Party|count|
+-----------------+-----+
|          Unknown| 3573|
|       Republican| 2213|
|     Non-Partisan| 1399|
|       Democratic| 1181|
|     Independence|  274|
|      Libertarian|   90|
|            Other|   25|
|Green Libertarian|   13|
```

```
|     Constitution|    9|
+-----------------+-----+
```

[227]:
```
alaskans_shooting.show()
```

```
+-----------------+-----+
|            Party|count|
+-----------------+-----+
|          Unknown|59092|
|       Republican|41730|
|     Non-Partisan|21653|
|       Democratic|16458|
|     Independence| 4645|
|      Libertarian| 1383|
|            Other|  348|
|Green Libertarian|  302|
|     Constitution|  133|
+-----------------+-----+
```

[228]:
```
dc_gamers = dc.filter(dc.EGame_Interest == "Yes")\
.groupby("Party").count().sort('count', ascending=False)

dc_shooting = dc.filter(dc.Interest_in_shooting == "Yes")\
.groupby("Party").count().sort('count', ascending=False)
```

[229]:
```
dc_gamers.show()
```

```
+------------+-----+
|       Party|count|
+------------+-----+
|  Democratic| 3993|
|Non-Partisan|  545|
|  Republican|  246|
|       Green|   35|
|       Other|    8|
| Libertarian|    5|
+------------+-----+
```

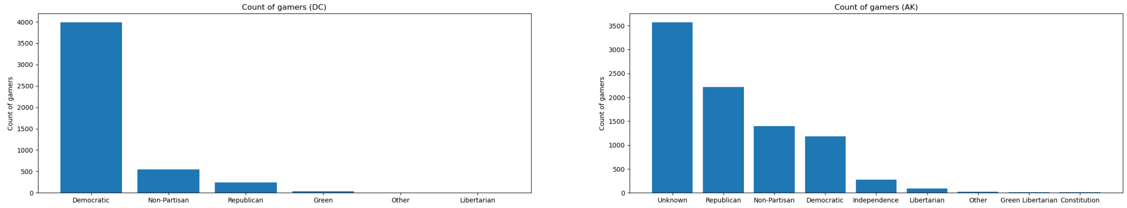
[230]:
```
dc_shooting.show()
```

```
+------------+-----+
|       Party|count|
+------------+-----+
|  Democratic|13591|
|Non-Partisan| 1899|
```

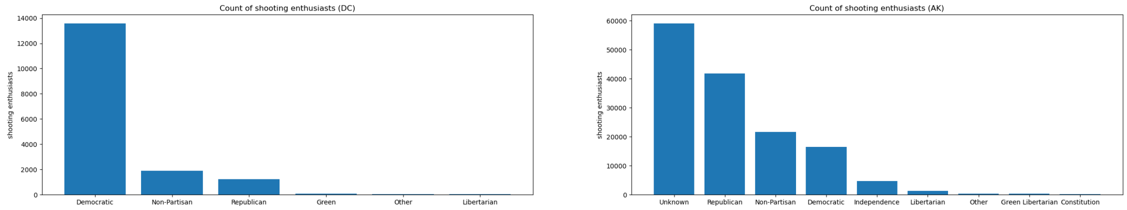
```
|  Republican| 1241|
|       Green|  101|
|       Other|   33|
| Libertarian|   31|
+------------+-----+
```

[231]:
```python
alaskans_gamers = alaskans_gamers.toPandas()
alaskans_shooting = alaskans_shooting.toPandas()

dc_gamers = dc_gamers.toPandas()
dc_shooting = dc_shooting.toPandas()
```

[232]:
```python
fig, ax = plt.subplots(1, 2)
fig.set_size_inches(30, 5)
ax[0].bar(dc_gamers['Party'], dc_gamers['count'])
ax[0].set_ylabel('Count of gamers')
ax[0].set_title('Count of gamers (DC)')
ax[1].bar(alaskans_gamers['Party'], alaskans_gamers['count'])
ax[1].set_ylabel('Count of gamers')
ax[1].set_title('Count of gamers (AK)')
plt.show()
```



[233]:
```python
fig, ax = plt.subplots(1, 2)
fig.set_size_inches(30, 5)
ax[0].bar(dc_shooting['Party'], dc_shooting['count'])
ax[0].set_ylabel('shooting enthusiasts')
ax[0].set_title('Count of shooting enthusiasts (DC)')
ax[1].bar(alaskans_shooting['Party'], alaskans_shooting['count'])
ax[1].set_ylabel('shooting enthusiasts')
ax[1].set_title('Count of shooting enthusiasts (AK)')
plt.show()
```



1) Comparing the proportion of gamers who are more likely to vote between DC and Alaska
2) Comparing the proportion of shooting enthusiasts who are more likely to vote between DC and Alaska

[234]:
```
alaskans_gamers1 = ak.filter(ak.EGame_Interest == "Yes")\
.groupby("Primary_Proportion_Voted").count()

alaskans_shooting1 = ak.filter(ak.Interest_in_shooting == "Yes")\
.groupby("Primary_Proportion_Voted").count()
```

[235]:
```
alaskans_gamers1.show()
```

```
+------------------------+-----+
|Primary_Proportion_Voted|count|
+------------------------+-----+
|                     33%|  113|
|                     66%|   34|
|                     83%|   12|
|                      0%| 3374|
|                     85%|  576|
|                     57%|  625|
|                     71%|  564|
|                    100%|  735|
|                     20%|   64|
|                     80%|   17|
|                     16%|   80|
|                     60%|   20|
|                     25%|  116|
|                     75%|   24|
|                     42%|  615|
|                     28%|  673|
|                     50%|  152|
|                     14%|  856|
|            Not Eligible|   76|
|                     40%|   51|
+------------------------+-----+
```

[236]:
```
alaskans_shooting1.show()
```

```
+------------------------+-----+
|Primary_Proportion_Voted|count|
+------------------------+-----+
|                     33%| 1982|
|                     66%|  740|
```

```
|                     83%|  196|
|                      0%|55065|
|                     85%| 9316|
|                     57%|10502|
|                     71%| 9930|
|                    100%|11022|
|                     20%| 1367|
|                     80%|  251|
|                     16%| 1450|
|                     60%|  411|
|                     25%| 1954|
|                     75%|  370|
|                     42%|11165|
|                     28%|11642|
|                     50%| 2645|
|                     14%|13600|
|            Not Eligible| 1426|
|                     40%|  710|
+------------------------+-----+
```

[237]:
```
alaskans_gamers1 = alaskans_gamers1.
 ↪select(regexp_replace(col("Primary_Proportion_Voted"), "%", "")
                                                             .
 ↪alias("Primary_Proportion_Voted"),col("count"))
alaskans_gamers1 = alaskans_gamers1.withColumn("Primary_Proportion_Voted",␣
 ↪col("Primary_Proportion_Voted").cast(LongType()))
alaskans_gamers_vote = alaskans_gamers1.filter(alaskans_gamers1.
 ↪Primary_Proportion_Voted>50)
alaskans_gamers_vote = alaskans_gamers_vote.withColumnRenamed("count", "gamers")
```

The number of gamers who have a high probability to vote

[238]:
```
alaskans_gamers_vote.agg({"gamers": "sum"}).show()
```

```
+-----------+
|sum(gamers)|
+-----------+
|       2607|
+-----------+
```

Total number of gamers

[239]:
```
alaskans_gamers1.agg({"count": "sum"}).show()
```

```
+----------+
|sum(count)|
+----------+
```

```
|       8777|
+-----------+
```

The percentage of gamers who are likely to vote

[240]:
```
2607/8777
```

[240]:
```
0.29702631878774066
```

[241]:
```
alaskans_shooting1 = alaskans_shooting1.
 ↪select(regexp_replace(col("Primary_Proportion_Voted"), "%", "")
                                                    .
 ↪alias("Primary_Proportion_Voted"),col("count"))
alaskans_shooting1 = alaskans_shooting1.withColumn("Primary_Proportion_Voted",␣
 ↪col("Primary_Proportion_Voted").cast(LongType()))
alaskans_shooting_voters = alaskans_shooting1.filter(alaskans_shooting1.
 ↪Primary_Proportion_Voted>50)
alaskans_shooting_voters = alaskans_shooting_voters.withColumnRenamed("count",␣
 ↪"shooters")
```

[242]:
```
alaskans_shooting1.show()
```

```
+------------------------+-----+
|Primary_Proportion_Voted|count|
+------------------------+-----+
|                      33| 1982|
|                      66|  740|
|                      83|  196|
|                       0|55065|
|                      85| 9316|
|                      57|10502|
|                      71| 9930|
|                     100|11022|
|                      20| 1367|
|                      80|  251|
|                      16| 1450|
|                      60|  411|
|                      25| 1954|
|                      75|  370|
|                      42|11165|
|                      28|11642|
|                      50| 2645|
|                      14|13600|
|                    null| 1426|
|                      40|  710|
+------------------------+-----+
```

[243]:
```
alaskans_shooting_voters.show()
```

```
+------------------------+--------+
|Primary_Proportion_Voted|shooters|
+------------------------+--------+
|                      66|     740|
|                      83|     196|
|                      85|    9316|
|                      57|   10502|
|                      71|    9930|
|                     100|   11022|
|                      80|     251|
|                      60|     411|
|                      75|     370|
+------------------------+--------+
```

Finding the amount of alaskans who are interested in shooting and are more likely to vote

[244]:
```
alaskans_shooting_voters.agg({"shooters": "sum"}).show()
```

```
+-------------+
|sum(shooters)|
+-------------+
|        42738|
+-------------+
```

Total amount of alaskans interested in shooting

[245]:
```
alaskans_shooting1.agg({"count": "sum"}).show()
```

```
+----------+
|sum(count)|
+----------+
|    145744|
+----------+
```

The percentage of alaskans interested in shooting who are likely to vote

[246]:
```
42738/145744
```

[246]: 0.2932402019980239

[247]:
```
dc_gamers1 = dc.filter(dc.EGame_Interest == "Yes")\
.groupby("Primary_Proportion_Voted").count()

dc_shooting1 = dc.filter(dc.Interest_in_shooting == "Yes")\
```

```
.groupby("Primary_Proportion_Voted").count()
```

[248]:
```
dc_gamers1.show()
```

```
+------------------------+-----+
|Primary_Proportion_Voted|count|
+------------------------+-----+
|                     33%|   65|
|                     66%|   31|
|                     83%|    9|
|                      0%| 2054|
|                     85%|  269|
|                     57%|  278|
|                     71%|  271|
|                    100%|  318|
|                     20%|   25|
|                     16%|   56|
|                     60%|    7|
|                     25%|   41|
|                     75%|   16|
|                     42%|  322|
|                     28%|  371|
|                     50%|   69|
|                     14%|  519|
|            Not Eligible|   87|
|                     40%|   14|
|                     80%|   10|
+------------------------+-----+
```

[249]:
```
dc_shooting1.show()
```

```
+------------------------+-----+
|Primary_Proportion_Voted|count|
+------------------------+-----+
|                     33%|  373|
|                     66%|  188|
|                     83%|   32|
|                      0%| 5960|
|                     85%| 1147|
|                     57%| 1148|
|                     71%| 1185|
|                    100%| 1296|
|                     20%|  117|
|                     80%|   30|
|                     16%|  163|
|                     60%|   50|
```

```
|                     25%|  230|
|                     75%|   98|
|                     42%| 1193|
|                     28%| 1322|
|                     50%|  417|
|                     14%| 1600|
|            Not Eligible|  287|
|                     40%|   60|
+------------------------+-----+
```

Finding the amount of dc citizens who are interested in gaming and are more likely to vote

The percentage of dc citizens interested in shooting who are likely to vote

[250]:
```
dc_shooting1 = dc_shooting1.
↪select(regexp_replace(col("Primary_Proportion_Voted"), "%", "")
                                                                 .
↪alias("Primary_Proportion_Voted"),col("count"))
dc_shooting1 = dc_shooting1.withColumn("Primary_Proportion_Voted",␣
↪col("Primary_Proportion_Voted").cast(LongType()))
dc_shooting_vote = dc_shooting1.filter(dc_shooting1.Primary_Proportion_Voted>50)
dc_shooting_vote = dc_shooting_vote.withColumnRenamed("count", "shooters")
```

Finding the amount of dc citizens who are interested in shooting and are more likely to vote

[251]:
```
dc_shooting_vote.agg({"shooters": "sum"}).show()
```

```
+-------------+
|sum(shooters)|
+-------------+
|         5174|
+-------------+
```

Total amount of alaskans interested in shooting

So the percentage of both gamers and shooting enthusiasts who are more likely to vote in the presidential elections are relatively the same, around 30% in Alaska and slightly different in DC where only 25% of gamers are interested in voting in comparisson to 30% of shooters.

In both DC and Alaska the same percentage of shooting enthusiasts have a high likelyhood of voting. Meanwhile there are less gamers in DC who are interested in voting than in Alaska

0.1.6 MARITAL STATUS AND PARTY AFFILIATION

[252]:
```
df_AK1 = spark.read\
.format("csv")\
.option("header", "true")\
.option("nullValue", "NA")\
```

```
.option("delimiter", "\t")\
.option("inferSchema", "true")\
.load('gs://final-proj-135/notebooks/jupyter/VM2Uniform--AK--2021-02-03.tab')

df_DC1 = spark.read\
.format("csv")\
.option("header", "true")\
.option("nullValue", "NA")\
.option("delimiter", "\t")\
.option("inferSchema", "true")\
.load('gs://final-proj-135/notebooks/jupyter/VM2Uniform--DC--2021-01-30.tab')

akdf = df_AK1.select(['Voters_Gender', 'Voters_Age', 'Parties_Description',
                      'Ethnic_Description', "MaritalStatus_Description",␣
 ↪"CommercialDataLL_Home_Owner_Or_Renter",␣
 ↪'Voters_VotingPerformanceEvenYearPrimary'])
dcdf = df_DC1.select(['Voters_Gender', 'Voters_Age', 'Parties_Description',
                      'Ethnic_Description', "MaritalStatus_Description",␣
 ↪"CommercialDataLL_Home_Owner_Or_Renter",␣
 ↪'Voters_VotingPerformanceEvenYearPrimary'])

akrenamed = akdf.withColumnRenamed("Voters_Gender", "Gender")\
            .withColumnRenamed("Voters_Age", "Age")\
            .withColumnRenamed("Parties_Description", "Party")\
            .withColumnRenamed("Ethnic_Description", "Ethnicity")\
            .withColumnRenamed("MaritalStatus_Description", "MaritalStatus")\
            .withColumnRenamed("CommercialDataLL_Home_Owner_Or_Renter",␣
 ↪"HomeOwnerorRenter")\
            .withColumnRenamed("Voters_VotingPerformanceEvenYearPrimary",␣
 ↪"Primary Vote")

dcrenamed = dcdf.withColumnRenamed("Voters_Gender", "Gender")\
            .withColumnRenamed("Voters_Age", "Age")\
            .withColumnRenamed("Parties_Description", "Party")\
            .withColumnRenamed("Ethnic_Description", "Ethnicity")\
            .withColumnRenamed("MaritalStatus_Description", "MaritalStatus")\
            .withColumnRenamed("CommercialDataLL_Home_Owner_Or_Renter",␣
 ↪"HomeOwnerorRenter")\
            .withColumnRenamed("Voters_VotingPerformanceEvenYearPrimary",␣
 ↪"Primary Vote")
```

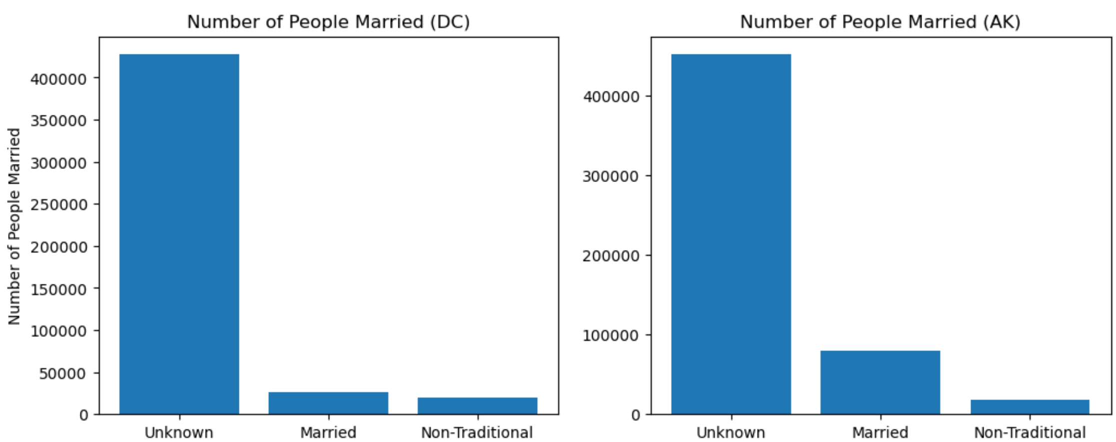
[253]:
```
DCMarried = dcrenamed.select('MaritalStatus', 'Party').groupby(dcrenamed.
 ↪MaritalStatus).count().sort("count", ascending=False)
DCMarried = DCMarried.toPandas()
DCMarried.fillna("Unknown",inplace=True)
```

```
AKMarried = akrenamed.select('MaritalStatus', 'Party').groupby(akrenamed.
 ↪MaritalStatus).count().sort("count", ascending=False)
AKMarried = AKMarried.toPandas()
AKMarried.fillna("Unknown",inplace=True)

DCMarried
AKMarried
```

[253]:

	MaritalStatus	count
0	Unknown	451313
1	Married	79352
2	Non-Traditional	17594

[254]:
```
fig, ax = plt.subplots(1, 2)
fig.set_size_inches(12, 4.5)
ax[0].bar(DCMarried['MaritalStatus'], DCMarried['count'])
ax[0].set_ylabel('Number of People Married')
ax[0].set_title('Number of People Married (DC)')
ax[1].bar(AKMarried['MaritalStatus'], AKMarried['count'])
ax[1].set_title('Number of People Married (AK)')
plt.show()
```



[255]:
```
DCMarriage = dcrenamed.select('Party', 'MaritalStatus').groupby(dcrenamed.
 ↪Party).count().sort("count", ascending=False)
DCMarriage = DCMarriage.toPandas()
DCMarriage.fillna("Unknown",inplace=True)

AKMarriage = akrenamed.select('Party', 'MaritalStatus').groupby(akrenamed.
 ↪Party).count().sort("count", ascending=False)
```

```
AKMarriage = AKMarriage.toPandas()
AKMarriage.fillna("Unknown",inplace=True)
```

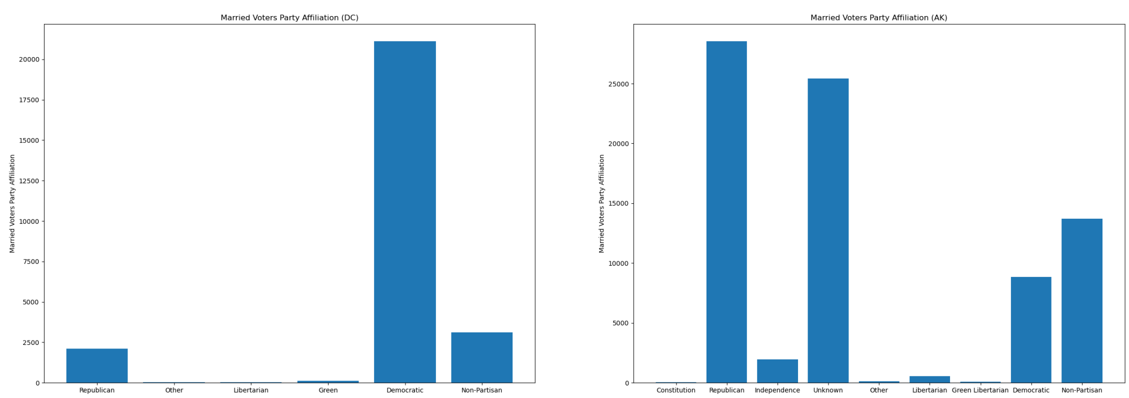
[256]:
```
akrenamed.select('Party').where('Party == "Unknown"').count()
```

[256]: 237742

[257]:
```
DCMarriagefilter = dcrenamed.filter(dcrenamed.MaritalStatus == "Married").
 ↪groupby("Party").count()

AKMarriagefilter = akrenamed.filter(akrenamed.MaritalStatus == "Married").
 ↪groupby("Party").count()

DCMarriagefilter.show()
AKMarriagefilter.show()

DCMarriagefilter = DCMarriagefilter.toPandas()
AKMarriagefilter = AKMarriagefilter.toPandas()

fig, ax = plt.subplots(1, 2)
fig.set_size_inches(30, 10)
ax[0].bar(DCMarriagefilter['Party'], DCMarriagefilter['count'])
ax[0].set_ylabel('Married Voters Party Affiliation')
ax[0].set_title('Married Voters Party Affiliation (DC)')
ax[1].bar(AKMarriagefilter['Party'], AKMarriagefilter['count'])
ax[1].set_ylabel('Married Voters Party Affiliation')
ax[1].set_title('Married Voters Party Affiliation (AK)')
plt.show()
```

```
+------------+-----+
|       Party|count|
+------------+-----+
|  Republican| 2103|
|       Other|   37|
| Libertarian|   42|
|       Green|  129|
|  Democratic|21119|
|Non-Partisan| 3132|
+------------+-----+
```

```
+-----------------+-----+
|            Party|count|
+-----------------+-----+
|     Constitution|   46|
|       Republican|28545|
|     Independence| 1965|
|          Unknown|25436|
|            Other|  136|
|      Libertarian|  569|
|Green Libertarian|   83|
|       Democratic| 8861|
|     Non-Partisan|13711|
+-----------------+-----+
```



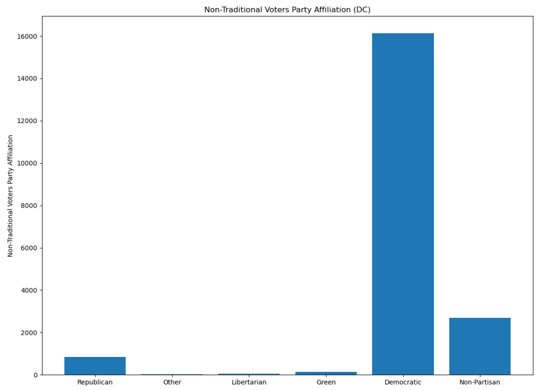
Voters who are married in DC tend to be Democratic whereas voters in AK tend to be Republican. However, AK has a lot of Unknown values which could be Democratic. ue to AK being a red state, it is unlikely.

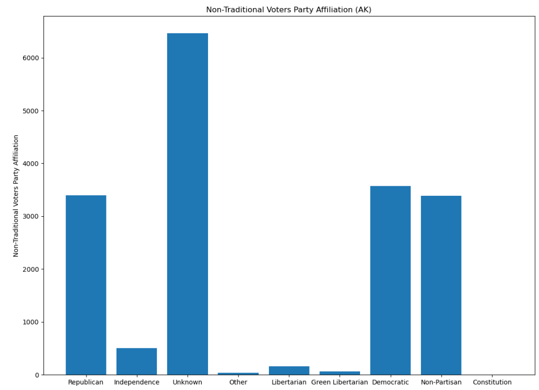
[258]:
```
DCNonTradfilter = dcrenamed.filter(dcrenamed.MaritalStatus ==␣
↪"Non-Traditional").groupby("Party").count()

AKNonTradfilter = akrenamed.filter(akrenamed.MaritalStatus ==␣
↪"Non-Traditional").groupby("Party").count()

DCNonTradfilter.show()
AKNonTradfilter.show()

DCNonTradfilter = DCNonTradfilter.toPandas()
AKNonTradfilter = AKNonTradfilter.toPandas()

fig, ax = plt.subplots(1, 2)
```

```python
fig.set_size_inches(30, 10)
ax[0].bar(DCNonTradfilter['Party'], DCNonTradfilter['count'])
ax[0].set_ylabel('Non-Traditional Voters Party Affiliation')
ax[0].set_title('Non-Traditional Voters Party Affiliation (DC)')
ax[1].bar(AKNonTradfilter['Party'], AKNonTradfilter['count'])
ax[1].set_ylabel('Non-Traditional Voters Party Affiliation')
ax[1].set_title('Non-Traditional Voters Party Affiliation (AK)')
plt.show()
```

```
+------------+-----+
|       Party|count|
+------------+-----+
|  Republican|  843|
|       Other|   27|
| Libertarian|   43|
|       Green|  139|
|  Democratic|16132|
|Non-Partisan| 2698|
+------------+-----+
```

```
+-----------------+-----+
|            Party|count|
+-----------------+-----+
|       Republican| 3396|
|     Independence|  507|
|          Unknown| 6464|
|            Other|   42|
|      Libertarian|  161|
|Green Libertarian|   66|
|       Democratic| 3569|
|     Non-Partisan| 3384|
|     Constitution|    5|
+-----------------+-----+
```





Non-Traditional Voters in DC lean towards Democratic in DC. In AK, Democratic party actually is higher than Republican by a small amount.

0.1.7 HOMEOWNERS AND PARTY AFFILIATION

[259]:
```
dcrenamed.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
 ↪dcrenamed.columns]).show()
akrenamed.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
 ↪akrenamed.columns]).show()
```

```
+------+------+-----+---------+-------------+----------------+------------+
|Gender|   Age|Party|Ethnicity|MaritalStatus|HomeOwnerorRenter|Primary Vote|
+------+------+-----+---------+-------------+----------------+------------+
| 19601|193536|    0|    37325|       427469|           71185|           0|
+------+------+-----+---------+-------------+----------------+------------+

[Stage 23263:==================================================>      (7 + 1) / 8]

+------+------+-----+---------+-------------+----------------+------------+
|Gender|   Age|Party|Ethnicity|MaritalStatus|HomeOwnerorRenter|Primary Vote|
+------+------+-----+---------+-------------+----------------+------------+
|    66|215368|    0|    71026|       451313|          198182|           0|
+------+------+-----+---------+-------------+----------------+------------+
```

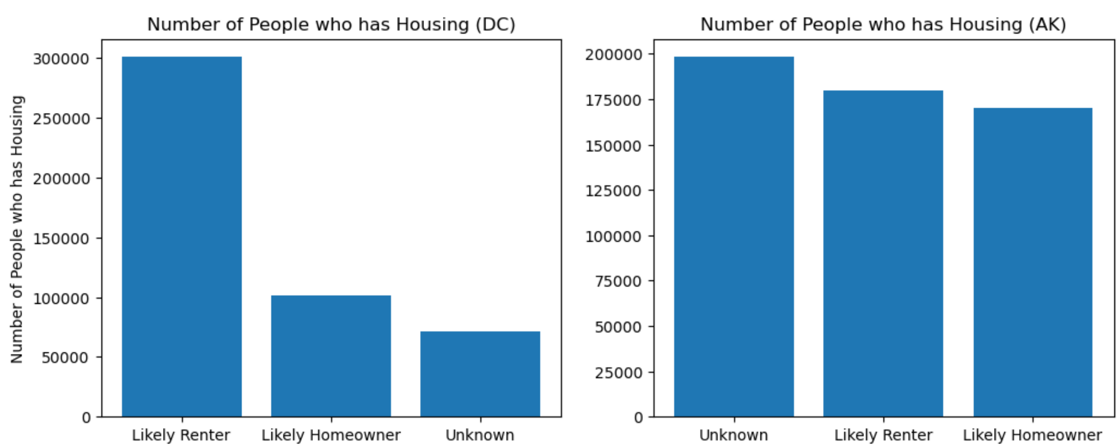
[260]:
```
DCOwner = dcrenamed.select('HomeOwnerorRenter', 'Party').groupby(dcrenamed.
 ↪HomeOwnerorRenter).count().sort("count", ascending=False)
DCOwner = DCOwner.toPandas()
DCOwner.fillna("Unknown",inplace=True)
```

```
AKOwner = akrenamed.select('HomeOwnerorRenter', 'Party').groupby(akrenamed.
↪HomeOwnerorRenter).count().sort("count", ascending=False)
AKOwner = AKOwner.toPandas()
AKOwner.fillna("Unknown",inplace=True)

DCOwner
AKOwner
```

[260]:

	HomeOwnerorRenter	count
0	Unknown	198182
1	Likely Renter	179858
2	Likely Homeowner	170219

[261]:
```
fig, ax = plt.subplots(1, 2)
fig.set_size_inches(12, 4.5)
ax[0].bar(DCOwner['HomeOwnerorRenter'], DCOwner['count'])
ax[0].set_ylabel('Number of People who has Housing')
ax[0].set_title('Number of People who has Housing (DC)')
ax[1].bar(AKOwner['HomeOwnerorRenter'], AKOwner['count'])
ax[1].set_title('Number of People who has Housing (AK)')
plt.show()
```

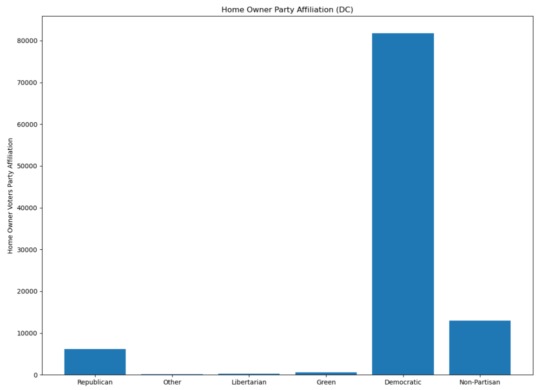


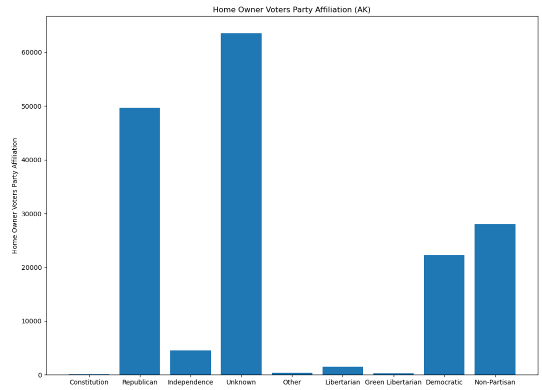
[262]:
```
DCHomeOwner = dcrenamed.filter(dcrenamed.HomeOwnerorRenter == "Likely␣
↪Homeowner").groupby("Party").count()

AKHomeOwner = akrenamed.filter(akrenamed.HomeOwnerorRenter == "Likely␣
↪Homeowner").groupby("Party").count()

DCHomeOwner.show()
```

```python
AKHomeOwner.show()

DCHomeOwner = DCHomeOwner.toPandas()
AKHomeOwner = AKHomeOwner.toPandas()

fig, ax = plt.subplots(1, 2)
fig.set_size_inches(30, 10)
ax[0].bar(DCHomeOwner['Party'], DCHomeOwner['count'])
ax[0].set_ylabel('Home Owner Voters Party Affiliation')
ax[0].set_title('Home Owner Party Affiliation (DC)')
ax[1].bar(AKHomeOwner['Party'], AKHomeOwner['count'])
ax[1].set_ylabel('Home Owner Voters Party Affiliation')
ax[1].set_title('Home Owner Voters Party Affiliation (AK)')
plt.show()
```

```
+------------+-----+
|       Party|count|
+------------+-----+
|  Republican| 6109|
|       Other|  179|
| Libertarian|  242|
|       Green|  585|
|  Democratic|81777|
|Non-Partisan|12958|
+------------+-----+
```

```
+-----------------+-----+
|            Party|count|
+-----------------+-----+
|     Constitution|   86|
|       Republican|49623|
|     Independence| 4534|
|          Unknown|63526|
|            Other|  367|
|      Libertarian| 1474|
|Green Libertarian|  312|
|       Democratic|22280|
|     Non-Partisan|28017|
+-----------------+-----+
```





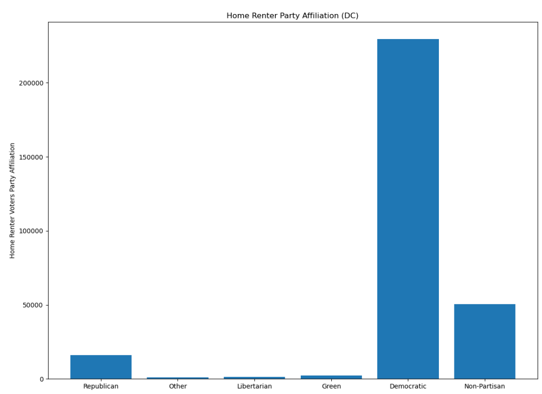
Home Owners in DC are more Democratic but Home Owners in AK are more Republican.

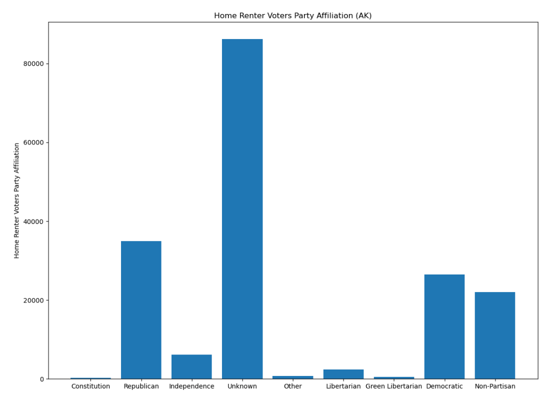
[263]:
```
DCHomeRenter = dcrenamed.filter(dcrenamed.HomeOwnerorRenter == "Likely Renter").
 ↪groupby("Party").count()

AKHomeRenter = akrenamed.filter(akrenamed.HomeOwnerorRenter == "Likely Renter").
 ↪groupby("Party").count()

DCHomeRenter.show()
AKHomeRenter.show()

DCHomeRenter = DCHomeRenter.toPandas()
AKHomeRenter = AKHomeRenter.toPandas()

fig, ax = plt.subplots(1, 2)
fig.set_size_inches(30, 10)
ax[0].bar(DCHomeRenter['Party'], DCHomeRenter['count'])
ax[0].set_ylabel('Home Renter Voters Party Affiliation')
ax[0].set_title('Home Renter Party Affiliation (DC)')
ax[1].bar(AKHomeRenter['Party'], AKHomeRenter['count'])
ax[1].set_ylabel('Home Renter Voters Party Affiliation')
ax[1].set_title('Home Renter Voters Party Affiliation (AK)')
plt.show()
```

```
+------------+------+
|       Party| count|
+------------+------+
|  Republican| 16024|
|       Other|  1044|
| Libertarian|  1329|
|       Green|  2382|
|  Democratic|229504|
```

```
|Non-Partisan| 50595|
+------------+------+
```

```
+-----------------+-----+
|            Party|count|
+-----------------+-----+
|     Constitution|  257|
|       Republican|34999|
|     Independence| 6189|
|          Unknown|86216|
|            Other|  762|
|      Libertarian| 2434|
|Green Libertarian|  530|
|       Democratic|26453|
|     Non-Partisan|22018|
+-----------------+-----+
```





Home Renters are more Democratic in DC but there is a smaller gap between the Republican Party and Democratic Party in AK.

0.2 First Attempt At Fitting Models

We decided to keep all the columns we have selected for EDA. For the sake of efficiency and accuracy, we have decided to drop all rows that do not have values for Age, Gender, Ethnicity, and Religion as we believe these will be important for classification. We have also decided to filter ethnicity and religion to contain only the top five of both and label all the other ethnicity and religion as “Other” so we can minimize computation time for the models.

[264]:

```
df_DC = df_DC.drop('Birthdate', 'Military_Status', 'Primary2020',␣
↪'Primary_Proportion_Voted')
df_AK = df_AK.drop('Birthdate', 'Military_Status', 'Primary2020',␣
↪'Primary_Proportion_Voted')
df_DC = df_DC.na.fill(value = 'Unknown', subset = 'Home_Owner_Or_Renter')
df_AK = df_AK.na.fill(value = 'Unknown', subset = 'Home_Owner_Or_Renter')
df_DC = df_DC.dropna(subset=['Age', 'Gender', 'Ethnicity', 'Religion'])
df_AK = df_AK.dropna(subset=['Age', 'Gender', 'Ethnicity', 'Religion'])
df_DC = df_DC.withColumn("Ethnicity", when(df_DC.Ethnicity == 'Likely Af-Am␣
↪(Modeled)', 'Likely Af-Am (Modeled)') \
                          .when(df_DC.Ethnicity == 'English/Welsh', 'English/
↪Welsh') \
                          .when(df_DC.Ethnicity == 'Hispanic', 'Hispanic') \
                          .when(df_DC.Ethnicity == 'German', 'German') \
                          .when(df_DC.Ethnicity == 'Irish', 'Irish') \
                          .when(df_DC.Ethnicity == 'Unknown', 'Unknown') \
                          .otherwise('Other'))
df_AK = df_AK.withColumn("Ethnicity", when(df_AK.Ethnicity == 'English/Welsh',␣
↪'English/Welsh') \
                          .when(df_AK.Ethnicity == 'German', 'German') \
                          .when(df_AK.Ethnicity == 'Irish', 'Irish') \
                          .when(df_AK.Ethnicity == 'Hispanic', 'Hispanic') \
                          .when(df_AK.Ethnicity == 'Scots', 'Scots') \
                          .otherwise('Other'))
df_DC = df_DC.withColumn("Religion", when(df_DC.Religion == 'Protestant',␣
↪'Protestant') \
                          .when(df_DC.Religion == 'Jewish', 'Jewish') \
                          .when(df_DC.Religion == 'Catholic', 'Catholic') \
                          .when(df_DC.Religion == 'Islamic', 'Islamic') \
                          .when(df_DC.Religion == 'Buddhist', 'Buddhist') \
                          .when(df_DC.Religion == 'Unknown', 'Unknown') \
                          .otherwise('Other'))
df_AK = df_AK.withColumn("Religion", when(df_AK.Religion == 'Protestant',␣
↪'Protestant') \
                          .when(df_AK.Religion == 'Jewish', 'Jewish') \
                          .when(df_AK.Religion == 'Catholic', 'Catholic') \
                          .when(df_AK.Religion == 'Eastern Orthodox', 'Eastern␣
↪Orthodox') \
                          .when(df_AK.Religion == 'Christian', 'Christian') \
                          .otherwise('Other'))
```

[265]:
```
df_AK.count()
```

[265]: 139165

[266]:
```
df_DC.count()
```

[266]: 114306

0.2.1 Logistic Regression

0.2.2 DC Model

[267]:
```
supervised = RFormula(formula="Party ~ .")
fittedRF_LDC = supervised.fit(df_DC)
preparedDF_LDC = fittedRF_LDC.transform(df_DC)
train2, test2 = preparedDF_LDC.randomSplit([0.7, 0.3], seed=333)
lrD = LogisticRegression(labelCol="label", featuresCol="features")
lrModelD = lrD.fit(train2)
fittedTest2 = lrModelD.transform(test2)
y_true = fittedTest2.select(['label']).collect()
y_pred = fittedTest2.select(['prediction']).collect()
confusion_matrix(y_true, y_pred)
```

[267]:
```
array([[28327,     0,     0,     0,     0,     0],
       [ 3771,     0,     0,     0,     0,     0],
       [ 1635,     0,     0,     0,     0,     0],
       [  237,     0,     0,     0,     0,     0],
       [   63,     0,     0,     0,     0,     0],
       [   48,     0,     0,     0,     0,     0]])
```

[268]:
```
print(classification_report(y_true, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.83      1.00      0.91     28327
         1.0       0.00      0.00      0.00      3771
         2.0       0.00      0.00      0.00      1635
         3.0       0.00      0.00      0.00       237
         4.0       0.00      0.00      0.00        63
         5.0       0.00      0.00      0.00        48

    accuracy                           0.83     34081
   macro avg       0.14      0.17      0.15     34081
weighted avg       0.69      0.83      0.75     34081
```

0.2.3 Alaska Model

[269]:
```
supervised = RFormula(formula="Party ~ .")
fittedRF_LAK = supervised.fit(df_AK)
preparedDF_LAK = fittedRF_LAK.transform(df_AK)
train1, test1 = preparedDF_LAK.randomSplit([0.7, 0.3], seed=333)
```

```
lrA = LogisticRegression(labelCol="label", featuresCol="features")
lrModelA = lrA.fit(train1)
fittedTest1 = lrModelA.transform(test1)
y_true = fittedTest1.select(['label']).collect()
y_pred = fittedTest1.select(['prediction']).collect()
confusion_matrix(y_true, y_pred)
```

[269]:
```
array([[10239,  4055,   104,   147,     0,     0,     0,     0,     0],
       [ 6863,  5132,    97,   120,     0,     0,     0,     0,     0],
       [ 4138,  2922,   104,   110,     0,     0,     0,     0,     0],
       [ 4005,  1666,    81,   139,     0,     0,     0,     0,     0],
       [  738,   333,    14,    20,     0,     0,     0,     0,     0],
       [  272,    62,     3,     1,     0,     0,     0,     0,     0],
       [   63,    12,     1,     0,     0,     0,     0,     0,     0],
       [   64,    17,     0,     0,     0,     0,     0,     0,     0],
       [   13,     6,     0,     0,     0,     0,     0,     0,     0]])
```

[270]:
```
print(classification_report(y_true, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.39      0.70      0.50     14545
         1.0       0.36      0.42      0.39     12212
         2.0       0.26      0.01      0.03      7274
         3.0       0.26      0.02      0.04      5891
         4.0       0.00      0.00      0.00      1105
         5.0       0.00      0.00      0.00       338
         6.0       0.00      0.00      0.00        76
         7.0       0.00      0.00      0.00        81
         8.0       0.00      0.00      0.00        19

    accuracy                           0.38     41541
   macro avg       0.14      0.13      0.11     41541
weighted avg       0.32      0.38      0.30     41541
```

However, after several simple experiments, we found that because the data is too unbalanced, our model will label most of the voters as the most popular party. Therefore, we decided to shorten the dataset and train the models with more balanced data.

1 Shortening Dataset

We kept all the features that we have explored, and we decided to add a feature that can represent the location information of the voter since we found that this can improve both the accuracy and f1 score of our models. In DC, we add the column 'Residence_Addresses_Zip', and in Alaska, we add the column 'County'.

```
[271]: from pyspark.sql.functions import *
import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
from functools import reduce
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder,␣
 ↪CrossValidatorModel
from pyspark.ml.feature import RFormula
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪ConfusionMatrixDisplay
import warnings
warnings.filterwarnings('ignore')
```

1.0.1 DC Data

```
[272]: # Read in DC Data
DC = spark.read\
.format("csv")\
.option("header", "true")\
.option("nullValue", "NA")\
.option("delimiter", "\t")\
.option("inferSchema", "true")\
.load('gs://final-proj-135/notebooks/jupyter/VM2Uniform--DC--2021-01-30.tab')
```

```
[273]: # Select feature columns
df_DC = DC.select(['Voters_Gender', 'Voters_Age', 'Parties_Description',␣
 ↪'Ethnic_Description',\
'Religions_Description', 'MaritalStatus_Description',␣
 ↪'CommercialDataLL_Gun_Owner',\
'CommercialDataLL_Home_Owner_Or_Renter',␣
 ↪'CommercialDataLL_Interest_in_Electronic_Gaming_In_Household', \
'CommercialDataLL_Interest_in_Shooting_In_Household',␣
 ↪'Residence_Addresses_Zip'])
```

```
[274]: df_DC = df_DC.cache()  # Cache the data
```

```
23/03/22 23:36:21 WARN org.apache.spark.sql.execution.CacheManager: Asked to
cache already cached data.
```

```
[275]: # Change the columns names
df_DC = df_DC.withColumnRenamed("Voters_Gender", "Gender")\
       .withColumnRenamed("Voters_Age", "Age")\
       .withColumnRenamed("Residence_Addresses_Zip", "Zip")\
```

```
        .withColumnRenamed("Ethnic_Description", "Ethnicity")\
        .withColumnRenamed("Religions_Description", "Religion")\
        .withColumnRenamed("MaritalStatus_Description", "Marital_Status")\
        .withColumnRenamed("CommercialDataLL_Gun_Owner", "Gun_Owner")\
        .withColumnRenamed("CommercialDataLL_Home_Owner_Or_Renter",␣
↪"Home_Owner_Or_Renter")\
        .
↪withColumnRenamed("CommercialDataLL_Interest_in_Electronic_Gaming_In_Household",␣
↪"EGame_Interest")\
        .withColumnRenamed("CommercialDataLL_Interest_in_Shooting_In_Household",␣
↪"Interest_in_shooting")\
        .withColumnRenamed("Parties_Description", "Party")
```

We convert the null values to "Unknown" or "No" for categorical data. We fill the mean of age in DC into the null value in "Age" column.

[276]:
```
df_DC = df_DC.na.fill(value = 53.3853, subset = 'Age')  # mean age
df_DC = df_DC.na.fill(value = 'Unknown', subset = 'Gender')
df_DC = df_DC.na.fill(value = 'Unknown', subset = 'Ethnicity')
df_DC = df_DC.na.fill(value = 'Unknown', subset = 'Religion')
df_DC = df_DC.na.fill(value = 'No', subset = 'Gun_Owner')
df_DC = df_DC.na.fill(value = 'No', subset = 'EGame_Interest')
df_DC = df_DC.na.fill(value = 'Not Married', subset = 'Marital_Status')
df_DC = df_DC.na.fill(value = 'No', subset = 'Interest_in_shooting')
df_DC = df_DC.na.fill(value = 'Unknown', subset = 'Home_Owner_Or_Renter')
df_DC = df_DC.na.fill(value = 'Unknown', subset = 'Zip')
```

Since different Zip code implies the voters live in different regions, we believe that convert the Zip code into string and make it become categorical data will be more helpful for the models.

[277]:
```
df_DC = df_DC.withColumn("Zip", df_DC.Zip.cast('string'))  # convert Zip to␣
↪string
```

[278]:
```
# Select top five ethnicities and religions and label the other as "Other"
df_DC = df_DC.withColumn("Ethnicity", when(df_DC.Ethnicity == 'Likely Af-Am␣
↪(Modeled)', 'Likely Af-Am (Modeled)') \
                            .when(df_DC.Ethnicity == 'English/Welsh', 'English/
↪Welsh') \
                            .when(df_DC.Ethnicity == 'Hispanic', 'Hispanic') \
                            .when(df_DC.Ethnicity == 'German', 'German') \
                            .when(df_DC.Ethnicity == 'Irish', 'Irish') \
                            .when(df_DC.Ethnicity == 'Unknown', 'Unknown') \
                            .otherwise('Other'))
df_DC = df_DC.withColumn("Religion", when(df_DC.Religion == 'Protestant',␣
↪'Protestant') \
                            .when(df_DC.Religion == 'Jewish', 'Jewish') \
                            .when(df_DC.Religion == 'Catholic', 'Catholic') \
```

```
                             .when(df_DC.Religion == 'Islamic', 'Islamic') \
                             .when(df_DC.Religion == 'Buddhist', 'Buddhist') \
                             .when(df_DC.Religion == 'Unknown', 'Unknown') \
                             .otherwise('Other'))
```

[279]:
```
DC_Party = df_DC.select('Party', 'Party').groupby(df_DC.Party).count().
 ↪sort("count", ascending=False)
DC_Party = DC_Party.toPandas()
DC_Party
```

[279]:

	Party	count
0	Democratic	365463
1	Non-Partisan	75549
2	Republican	26063
3	Green	3506
4	Libertarian	1884
5	Other	1448

Since only 1448 voters in DC registered for "Other" and 1884 voters in DC registered for "Libertarian", we will use all of the data from these two parties. We slightly increase the number of data from other parties to make the data not completely balanced. We select 2500 voters from Democratic, 2300 voters from Non-Partisan, 2200 voters from Republican, 2000 voters from Green, 1884 voters from Libertarian, and 1448 voters from Other.

[280]:
```
df_DC_1 = df_DC.filter(df_DC.Party == 'Democratic').limit(2500)
df_DC_2 = df_DC.filter(df_DC.Party == 'Non-Partisan').limit(2300)
df_DC_3 = df_DC.filter(df_DC.Party == 'Republican').limit(2200)
df_DC_4 = df_DC.filter(df_DC.Party == 'Green').limit(2000)
df_DC_5 = df_DC.filter(df_DC.Party == 'Libertarian').limit(1884)
df_DC_6 = df_DC.filter(df_DC.Party == 'Other').limit(1448)
dfs = [df_DC_1, df_DC_2, df_DC_3, df_DC_4, df_DC_5, df_DC_6]
df_DC = reduce(DataFrame.unionAll, dfs)
```

After shortening the dataset in DC, we will use 12332 data to train the model.

[281]:
```
df_DC.count()
```

[281]: 12332

Now, we use RFormula to generate labels and features for the dataset.

[282]:
```
DC_supervised = RFormula(formula="Party ~ .")
DC_fittedRF = DC_supervised.fit(df_DC)
DC_preparedDF = DC_fittedRF.transform(df_DC)
```

We randomly split the dataset into training and testing dataset. We select 70% data as training set and 30% data as testing set.

[283]:
```
DC_train, DC_test = DC_preparedDF.randomSplit([0.7, 0.3], seed=33)
```

The labels for different parties are displayed in the table below.

[284]:
```
DC_preparedDF.select('Party', 'label').distinct().show()
```

```
+------------+-----+
|       Party|label|
+------------+-----+
|  Democratic|  0.0|
|Non-Partisan|  1.0|
|  Republican|  2.0|
|       Green|  3.0|
| Libertarian|  4.0|
|       Other|  5.0|
+------------+-----+
```

The followings are the features we will use when training models for DC.

[285]:
```
DC_featureCols = pd.DataFrame(DC_preparedDF.schema["features"].
↪metadata["ml_attr"]["attrs"]["binary"]+
DC_preparedDF.schema["features"].metadata["ml_attr"]["attrs"]["numeric"]).
↪sort_values("idx")
DC_featureCols = DC_featureCols.set_index('idx')
```

[286]:
```
print(np.array(DC_featureCols).transpose())
```

```
[['Gender_M' 'Gender_F' 'Age' 'Ethnicity_Likely Af-Am (Modeled)'
  'Ethnicity_Other' 'Ethnicity_English/Welsh' 'Ethnicity_Unknown'
  'Ethnicity_Hispanic' 'Ethnicity_German' 'Religion_Unknown'
  'Religion_Protestant' 'Religion_Jewish' 'Religion_Catholic'
  'Religion_Other' 'Religion_Islamic' 'Marital_Status_Not Married'
  'Marital_Status_Married' 'Gun_Owner_No'
  'Home_Owner_Or_Renter_Likely Renter' 'Home_Owner_Or_Renter_Unknown'
  'EGame_Interest_No' 'Interest_in_shooting_No' 'Zip_20001' 'Zip_20037'
  'Zip_20002' 'Zip_20007' 'Zip_20011' 'Zip_20009' 'Zip_20052' 'Zip_20010'
  'Zip_20019' 'Zip_20003' 'Zip_20020' 'Zip_20016' 'Zip_20017' 'Zip_20008'
  'Zip_20018' 'Zip_20032' 'Zip_20006' 'Zip_20012' 'Zip_20015' 'Zip_20036'
  'Zip_20024' 'Zip_20005' 'Zip_20057' 'Zip_20059' 'Zip_20004' 'Zip_20500'
  'Zip_20373' 'Zip_20422' 'Zip_20431']]
```

1.0.2 Alaska Data

[287]:
```
# Read in AK Data
AK = spark.read\
.format("csv")\
.option("header", "true")\
```

```
.option("nullValue", "NA")\
.option("delimiter", "\t")\
.option("inferSchema", "true")\
.load('gs://final-proj-135/notebooks/jupyter/VM2Uniform--AK--2021-02-03.tab')
```

[288]:
```
# Select feature columns
df_AK = AK.select(['Voters_Gender', 'Voters_Age', 'Parties_Description',␣
 ↪'Ethnic_Description',\
'Religions_Description', 'MaritalStatus_Description',␣
 ↪'CommercialDataLL_Gun_Owner',\
'CommercialDataLL_Home_Owner_Or_Renter',␣
 ↪'CommercialDataLL_Interest_in_Electronic_Gaming_In_Household', \
'CommercialDataLL_Interest_in_Shooting_In_Household', 'County'])
```

[289]:
```
df_AK = df_AK.cache()  # Cache the data
```

```
23/03/22 23:37:02 WARN org.apache.spark.sql.execution.CacheManager: Asked to
cache already cached data.
```

[290]:
```
# Change the columns names
df_AK = df_AK.withColumnRenamed("Voters_Gender", "Gender")\
        .withColumnRenamed("Voters_Age", "Age")\
        .withColumnRenamed("Residence_Addresses_Zip", "Zip")\
        .withColumnRenamed("Ethnic_Description", "Ethnicity")\
        .withColumnRenamed("Religions_Description", "Religion")\
        .withColumnRenamed("MaritalStatus_Description", "Marital_Status")\
        .withColumnRenamed("CommercialDataLL_Gun_Owner", "Gun_Owner")\
        .withColumnRenamed("CommercialDataLL_Home_Owner_Or_Renter",␣
 ↪"Home_Owner_Or_Renter")\
        .
 ↪withColumnRenamed("CommercialDataLL_Interest_in_Electronic_Gaming_In_Household",␣
 ↪"EGame_Interest")\
        .withColumnRenamed("CommercialDataLL_Interest_in_Shooting_In_Household",␣
 ↪"Interest_in_shooting")\
        .withColumnRenamed("Parties_Description", "Party")
```

We convert the null values to "Unknown" or "No" for categorical data. We fill the mean of age in Alaska into the null value in "Age" column.

[291]:
```
df_AK = df_AK.na.fill(value = 54.6339, subset = 'Age')
df_AK = df_AK.na.fill(value = 'Unknown', subset = 'Gender')
df_AK = df_AK.na.fill(value = 'Unknown', subset = 'Ethnicity')
df_AK = df_AK.na.fill(value = 'Unknown', subset = 'Religion')
df_AK = df_AK.na.fill(value = 'No', subset = 'Gun_Owner')
df_AK = df_AK.na.fill(value = 'No', subset = 'EGame_Interest')
```

```
df_AK = df_AK.na.fill(value = 'Not Married', subset = 'Marital_Status')
df_AK = df_AK.na.fill(value = 'No', subset = 'Interest_in_shooting')
df_AK = df_AK.na.fill(value = 'Unknown', subset = 'Home_Owner_Or_Renter')
df_AK = df_AK.na.fill(value = 'Unknown', subset = 'County')
```

[292]:
```
# Select top five ethnicities and religions and label the other as "Other"
df_AK = df_AK.withColumn("Ethnicity", when(df_AK.Ethnicity == 'English/Welsh',␣
↪'English/Welsh') \
                              .when(df_AK.Ethnicity == 'German', 'German') \
                              .when(df_AK.Ethnicity == 'Irish', 'Irish') \
                              .when(df_AK.Ethnicity == 'Scots', 'Scots') \
                              .when(df_AK.Ethnicity == 'Hispanic', 'Hispanic') \
                              .when(df_AK.Ethnicity == 'Unknown', 'Unknown') \
                              .otherwise('Other'))
df_AK = df_AK.withColumn("Religion", when(df_AK.Religion == 'Protestant',␣
↪'Protestant') \
                              .when(df_AK.Religion == 'Catholic', 'Catholic') \
                              .when(df_AK.Religion == 'Jewish', 'Jewish') \
                              .when(df_AK.Religion == 'Eastern Orthodox', 'Eastern␣
↪Orthodox') \
                              .when(df_AK.Religion == 'Christian', 'Christian') \
                              .when(df_AK.Religion == 'Unknown', 'Unknown') \
                              .otherwise('Other'))
```

[293]:
```
AK_Party = df_AK.select('Party', 'Party').groupby(df_AK.Party).count().
↪sort("count", ascending=False)
AK_Party = AK_Party.toPandas()
AK_Party
```

[293]:

	Party	count
0	Unknown	237742
1	Republican	133370
2	Non-Partisan	75520
3	Democratic	73994
4	Independence	17667
5	Libertarian	6202
6	Other	1765
7	Green Libertarian	1406
8	Constitution	593

Since only 593 voters registered for Constitution, 1406 voters registered for Green Libertarian, and 1765 voters registered for Other, we will use all of the data from these three parties. We slightly increase the number of data from other parties to make the data not completely balanced. We select 2500 voters from Unknown, 2400 voters from Republican, 2300 voters from Non-Partisan, 2200 voters from Democratic, 2100 voters from Independence, and 2000 voters from Libertarian.

[294]:
```
df_AK_1 = df_AK.filter(df_AK.Party == 'Unknown').limit(2500)
df_AK_2 = df_AK.filter(df_AK.Party == 'Republican').limit(2400)
df_AK_3 = df_AK.filter(df_AK.Party == 'Non-Partisan').limit(2300)
df_AK_4 = df_AK.filter(df_AK.Party == 'Democratic').limit(2200)
df_AK_5 = df_AK.filter(df_AK.Party == 'Independence').limit(2100)
df_AK_6 = df_AK.filter(df_AK.Party == 'Libertarian').limit(2000)
df_AK_7 = df_AK.filter(df_AK.Party == 'Other').limit(1765)
df_AK_8 = df_AK.filter(df_AK.Party == 'Green Libertarian').limit(1406)
df_AK_9 = df_AK.filter(df_AK.Party == 'Constitution').limit(593)
dfs = [df_AK_1, df_AK_2, df_AK_3, df_AK_4, df_AK_5, df_AK_6, df_AK_7, df_AK_8,␣
↪df_AK_9]
df_AK = reduce(DataFrame.unionAll, dfs)
```

After shortening the dataset in Alaska, we will use 17264 data to train the model.

[295]:
```
df_AK.count()
```

[295]:
```
17264
```

Now, we use RFormula to generate labels and features for the dataset.

[296]:
```
AK_supervised = RFormula(formula="Party ~ .")
AK_fittedRF = AK_supervised.fit(df_AK)
AK_preparedDF = AK_fittedRF.transform(df_AK)
```

We randomly split the dataset into training and testing dataset. We select 70% data as training set and 30% data as testing set.

[297]:
```
AK_train, AK_test = AK_preparedDF.randomSplit([0.7, 0.3], seed=33)
```

The labels for different parties are displayed in the table below.

[298]:
```
AK_preparedDF.select('Party', 'label').distinct().show()
```

```
[Stage 24434:=============>                                           (2 + 1) / 8]

+-----------------+-----+
|            Party|label|
+-----------------+-----+
|          Unknown|  0.0|
|       Republican|  1.0|
|     Non-Partisan|  2.0|
|       Democratic|  3.0|
|     Independence|  4.0|
|      Libertarian|  5.0|
|            Other|  6.0|
```

```
|Green Libertarian|  7.0|
|     Constitution|  8.0|
+-----------------+-----+
```

The followings are the features we will use when training models for Alaska.

[299]:
```
AK_featureCols = pd.DataFrame(AK_preparedDF.schema["features"].
 ↪metadata["ml_attr"]["attrs"]["binary"]+
AK_preparedDF.schema["features"].metadata["ml_attr"]["attrs"]["numeric"]).
 ↪sort_values("idx")
AK_featureCols = AK_featureCols.set_index('idx')
```

[300]:
```
print(np.array(AK_featureCols).transpose())
```

```
[['Gender_M' 'Gender_F' 'Age' 'Ethnicity_English/Welsh' 'Ethnicity_Other'
  'Ethnicity_Unknown' 'Ethnicity_Hispanic' 'Ethnicity_German'
  'Ethnicity_Irish' 'Religion_Unknown' 'Religion_Protestant'
  'Religion_Catholic' 'Religion_Jewish' 'Religion_Eastern Orthodox'
  'Religion_Other' 'Marital_Status_Not Married' 'Marital_Status_Married'
  'Gun_Owner_No' 'Home_Owner_Or_Renter_Likely Renter'
  'Home_Owner_Or_Renter_Unknown' 'EGame_Interest_No'
  'Interest_in_shooting_No' 'County_ANCHORAGE' 'County_ALEUTIANS WEST'
  'County_ALEUTIANS EAST' 'County_MATANUSKA SUSITNA'
  'County_FAIRBANKS NORTH STAR' 'County_KENAI PENINSULA' 'County_JUNEAU'
  'County_BETHEL' 'County_KETCHIKAN GATEWAY' 'County_VALDEZ CORDOVA'
  'County_KODIAK ISLAND' 'County_SITKA' 'County_SOUTHEAST FAIRBANKS'
  'County_NOME' 'County_KUSILVAK' 'County_NORTHWEST ARCTIC'
  'County_PRINCE OF WALES HYDER' 'County_NORTH SLOPE' 'County_HAINES'
  'County_YUKON KOYUKUK' 'County_DENALI' 'County_PETERSBURG'
  'County_SKAGWAY' 'County_HOONAH ANGOON' 'County_WRANGELL'
  'County_DILLINGHAM' 'County_LAKE AND PENINSULA' 'County_BRISTOL BAY']]
```

2 Construct Models

We want to classify the voters' registered parties based on features such as gender, age, ethnicity, religion, location, and so on. There are 6 parties in DC and 9 parties in Alaska, so this is a multiclass classification problem. We will construct 4 models to solve the problem: logistic regression, decision tree, random forest, and naive bayes. We want to find what features that are important in the classification. We will use f1 score as the metric when we do the cross validation.

[148]:
```
evaluator = MulticlassClassificationEvaluator(metricName='f1')
```

[149]:
```
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml.classification import RandomForestClassifier
```

```
from pyspark.ml.classification import NaiveBayes
```

[150]:
```
lr = LogisticRegression(labelCol="label", featuresCol="features")
dt = DecisionTreeClassifier(labelCol="label", featuresCol="features")
rf = RandomForestClassifier(labelCol="label", featuresCol="features")
nb = NaiveBayes(labelCol = 'label', featuresCol = 'features')
```

2.1 Logistic Regression

In the logistic regression, we will tune elasticNetParam with values 0, 0.5, 1, and regParam with values 0, 0.1, 0.5.

2.1.1 DC

[151]:
```
# build ParamGrid
lr_params = ParamGridBuilder() \
  .addGrid(lr.elasticNetParam, [0, 0.5, 1]) \
  .addGrid(lr.regParam, [0, 0.1, 0.5]) \
  .build()
# build cross validator model
lr_cv = CrossValidator(estimator=lr, estimatorParamMaps=lr_params,␣
 ↪evaluator=evaluator, numFolds=3, seed=33)
```

[ ]:
```
DC_lr_cv = lr_cv.fit(DC_train)   # fit the model on the training set
```

[ ]:
```
DC_lr_cv.save('gs://final-proj-135/notebooks/jupyter/DC_lr_cv')   # save the␣
 ↪model
```

[455]:
```
lr_model = CrossValidatorModel.load('gs://final-proj-135/notebooks/jupyter/
 ↪DC_lr_cv')  # load the model
```

```
23/03/23 02:30:55 WARN org.apache.hadoop.util.concurrent.ExecutorHelper: Thread
(Thread[GetFileInfo #1,5,main]) interrupted:
java.lang.InterruptedException
        at
com.google.common.util.concurrent.AbstractFuture.get(AbstractFuture.java:510)
        at com.google.common.util.concurrent.FluentFuture$TrustedFuture.get(Flue
ntFuture.java:88)
        at org.apache.hadoop.util.concurrent.ExecutorHelper.logThrowableFromAfte
rExecute(ExecutorHelper.java:48)
        at org.apache.hadoop.util.concurrent.HadoopThreadPoolExecutor.afterExecu
te(HadoopThreadPoolExecutor.java:90)
        at
java.util.concurrent.ThreadPoolExecutor.runWorker(ThreadPoolExecutor.java:1157)
        at
java.util.concurrent.ThreadPoolExecutor$Worker.run(ThreadPoolExecutor.java:624)
        at java.lang.Thread.run(Thread.java:750)
```

[411]:
```
fittedTest = lr_model.transform(DC_test)  # fit the model on testing set
```

[412]:
```
print('accuracy: '+ str(evaluator.evaluate(fittedTest, {evaluator.metricName:␣
↪"accuracy"})))
print('f1: '+ str(evaluator.evaluate(fittedTest, {evaluator.metricName: "f1"})))
```

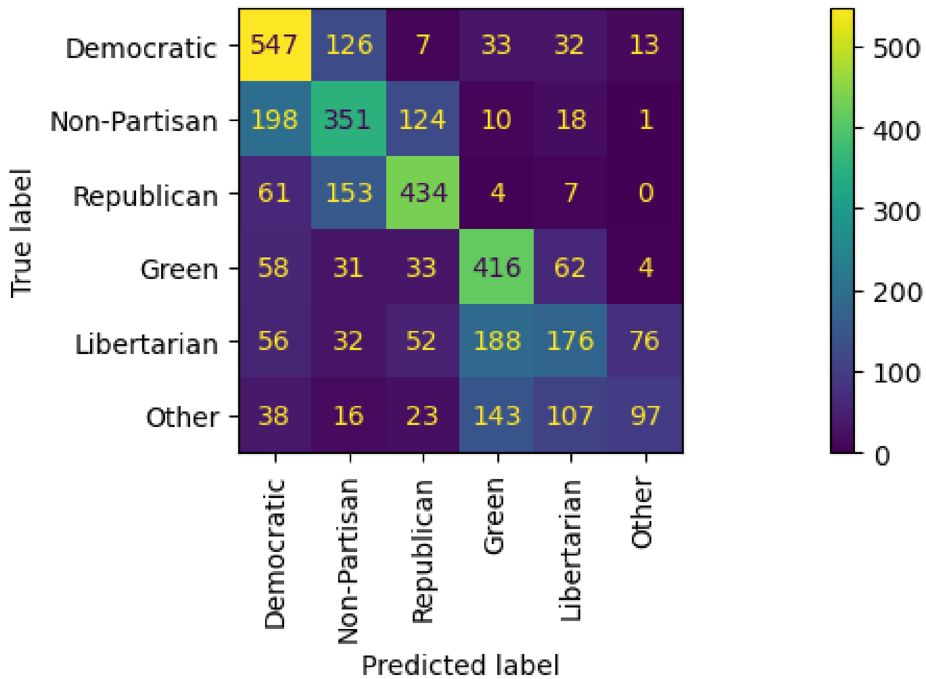
```
accuracy: 0.5422591896968071
[Stage 33912:================================>                       (4 + 1) / 7]
f1: 0.5267126721200518
```

After cross validation, the best f1 score for logistic regression in DC is around 0.5267 and the accuracy is around 0.5423. Now we plot the confusion matrix.

[413]:
```
y_true = fittedTest.select(['label']).collect()
y_pred = fittedTest.select(['prediction']).collect()
```

[414]:
```
DC_party_names =␣
↪['Democratic','Non-Partisan','Republican','Green','Libertarian','Other']
cm = confusion_matrix(y_true, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,␣
↪display_labels=DC_party_names)
disp.plot(xticks_rotation='vertical')
```

[414]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f558938feb0>
```



From the confusion matrix, we can notice that the number on the diagonal is the largest in each column, which implies the model is doing the classification.

[415]:
```
print(classification_report(y_true, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       0.57      0.72      0.64       758
         1.0       0.50      0.50      0.50       702
         2.0       0.64      0.66      0.65       659
         3.0       0.52      0.69      0.60       604
         4.0       0.44      0.30      0.36       580
         5.0       0.51      0.23      0.32       424

    accuracy                           0.54      3727
   macro avg       0.53      0.52      0.51      3727
weighted avg       0.53      0.54      0.53      3727
```

We can see that the f1 scores for Democratic and Republican are the highest, which means the model can classify these two parties better. The f1 scores for Libertarian and Other are relatively low. This is probobaly because the data from these two parties that are used to train the model is less than those of the other parties.

[416]:
```python
print(lr_model.bestModel.explainParams().split('\n')[1]) # elasticNetParam
print(lr_model.bestModel.explainParams().split('\n')[13]) # regParam
```

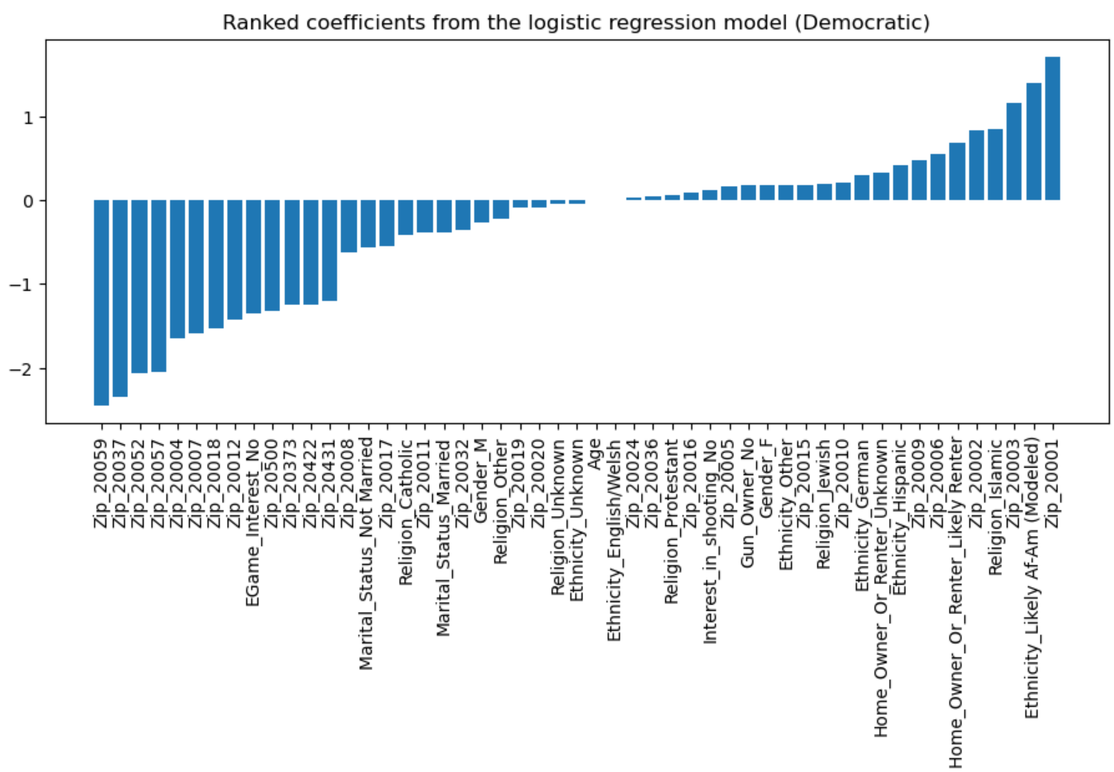
```
elasticNetParam: the ElasticNet mixing parameter, in range [0, 1]. For alpha =
0, the penalty is an L2 penalty. For alpha = 1, it is an L1 penalty. (default:
0.0, current: 0.0)
regParam: regularization parameter (>= 0). (default: 0.0, current: 0.0)
```

After cross validation, the best model has elasticNetParam=0 and regParam=0.

Now, we are going to analyze the feature importance in this logistic regression model.

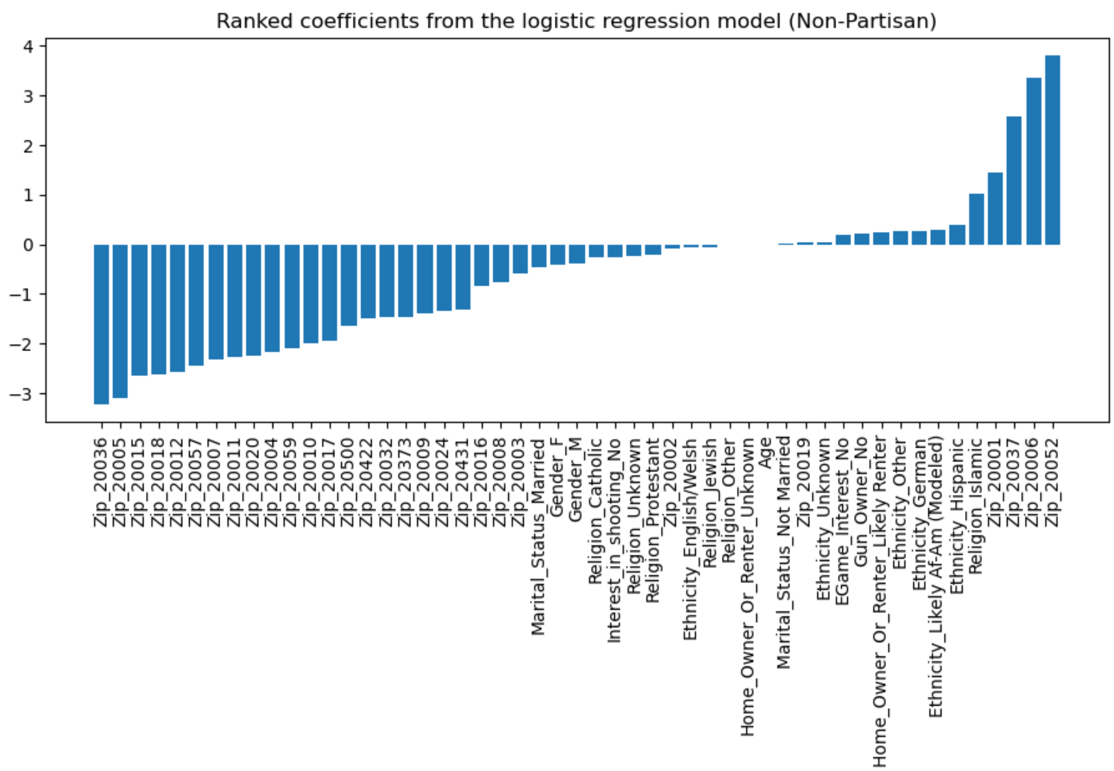
[417]:
```python
coefsArray = lr_model.bestModel.coefficientMatrix.toArray() # convert to np.
↪array
coefsDF = pd.DataFrame(coefsArray.transpose(), columns=DC_party_names) # to␣
↪pandas
coefsDF = coefsDF.merge(DC_featureCols, left_index=True, right_index=True)
```

[418]:
```python
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Democratic', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Democratic'])
plt.title('Ranked coefficients from the logistic regression model (Democratic)')
plt.show()
```



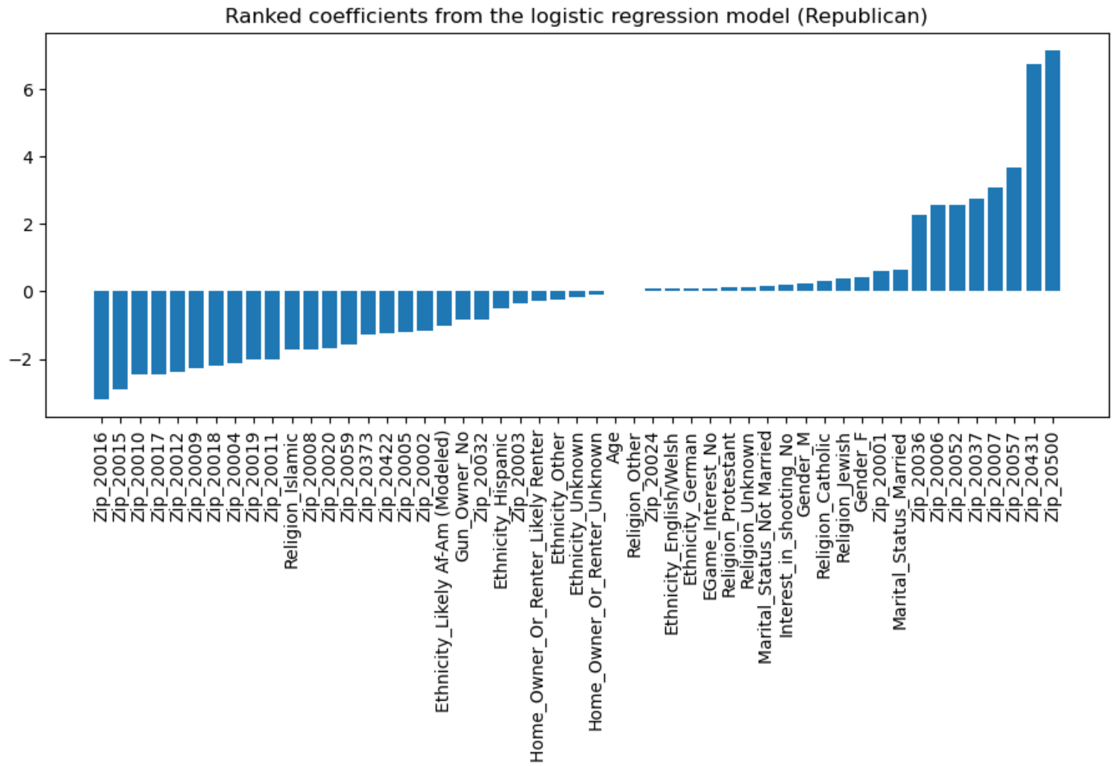
We can see that people who live in the area with zip code 20001, 20003, and with ethnicity Likely Af-Am (Modeled) are more likely to register for Democratic. People who live in the area with zip code 20059, 20037, and have no interest in EGame are less likely to register for Democratic.

[419]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Non-Partisan', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Non-Partisan'])
plt.title('Ranked coefficients from the logistic regression model␣
 ↪(Non-Partisan)')
plt.show()
```



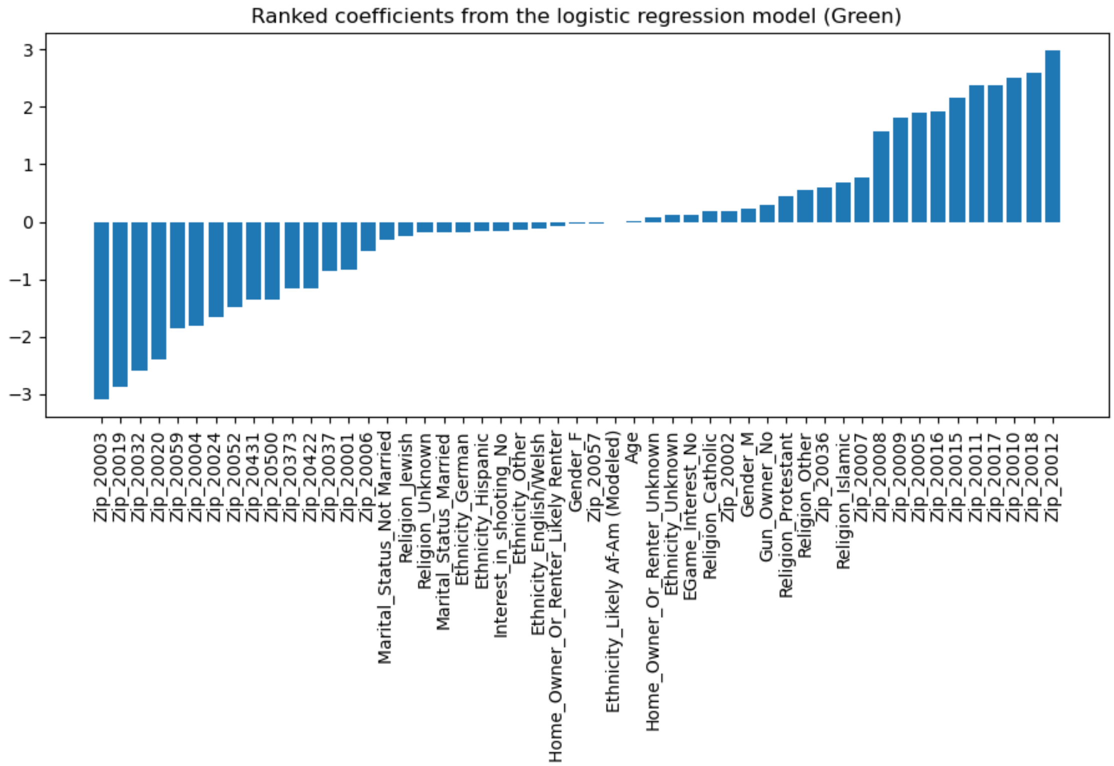
We can see that people who live in the area with zip code 20052, 20006, and with religion Islamic are more likely to register for Non-Partisan. People who live in the area with zip code 20036, 20005, and with married marital status are less likely to register for Non-Partisan.

[420]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Republican', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Republican'])
plt.title('Ranked coefficients from the logistic regression model (Republican)')
plt.show()
```



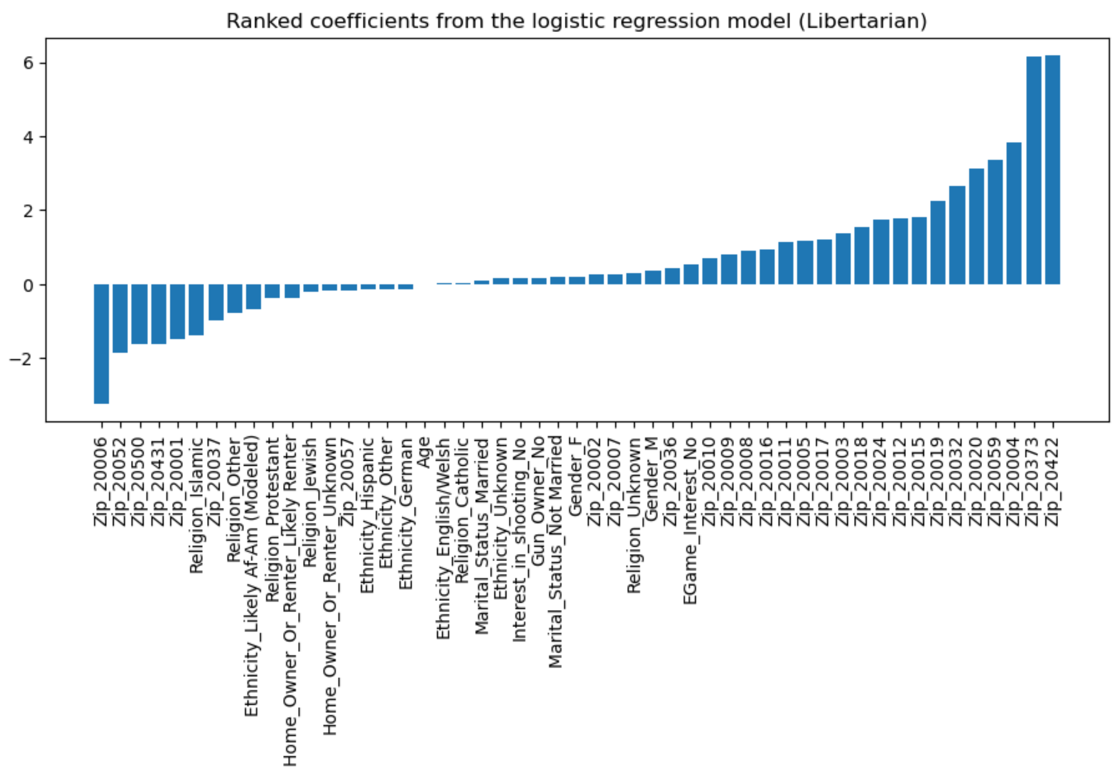
We can see that people who live in the area with zip code 20500, 20431, and with married marial status are more likely to register for Republican. People who live in the area with zip code 20016, 20015, and with religion Islamic are less likely to register for Republican.

[421]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Green', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Green'])
plt.title('Ranked coefficients from the logistic regression model (Green)')
plt.show()
```



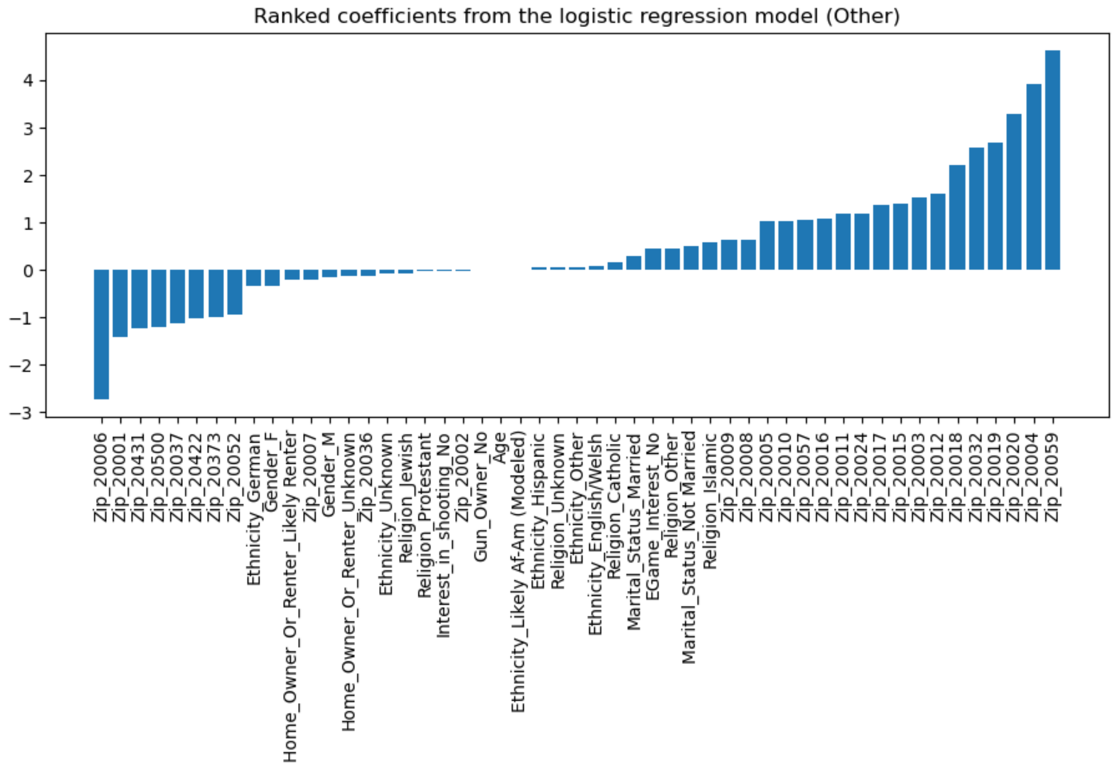
We can see that people who live in the area with zip code 20012, 20018, and with religion Islamic are more likely to register for Green. People who live in the area with zip code 20003, 20019, and with not married marital status are less likely to register for Green.

[422]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Libertarian', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Libertarian'])
plt.title('Ranked coefficients from the logistic regression model␣
↪(Libertarian)')
plt.show()
```



We can see that people who live in the area with zip code 20422, 20373, and 20004 are more likely to register for Libertarian. People who live in the area with zip code 20006, 20052, and with religion Islamic are less likely to register for Libertarian.

[423]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Other', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Other'])
plt.title('Ranked coefficients from the logistic regression model (Other)')
plt.show()
```



We can see that people who live in the area with zip code 20059, 20004, and 20020 are more likely to register for Other. People who live in the area with zip code 20006, 20001, and with ethnicity German are less likely to register for Other.

We now list the feature importance for different parties into table.

[424]:
```
DC_tmp = []
for i in DC_party_names:
    coefsDF.sort_values(i, ascending=False, inplace=True)
    DC_tmp.append(np.array(coefsDF.name))
```

[425]:
```
DC_tmp = pd.DataFrame(np.transpose(DC_tmp))
DC_tmp.columns = DC_party_names
DC_tmp.head()
```

[425]:
```
                        Democratic      Non-Partisan Republican      Green  \
0                        Zip_20001         Zip_20052  Zip_20500  Zip_20012
1  Ethnicity_Likely Af-Am (Modeled)        Zip_20006  Zip_20431  Zip_20018
2                        Zip_20003         Zip_20037  Zip_20057  Zip_20010
3                 Religion_Islamic         Zip_20001  Zip_20007  Zip_20017
4                        Zip_20002  Religion_Islamic  Zip_20037  Zip_20011

  Libertarian      Other
```

```
0   Zip_20422  Zip_20059
1   Zip_20373  Zip_20004
2   Zip_20004  Zip_20020
3   Zip_20059  Zip_20019
4   Zip_20020  Zip_20032
```

[426]:
```
DC_tmp.tail()
```

[426]:
```
   Democratic Non-Partisan Republican      Green Libertarian      Other
46  Zip_20004    Zip_20012  Zip_20012  Zip_20059   Zip_20001  Zip_20037
47  Zip_20057    Zip_20018  Zip_20017  Zip_20020   Zip_20431  Zip_20500
48  Zip_20052    Zip_20015  Zip_20010  Zip_20032   Zip_20500  Zip_20431
49  Zip_20037    Zip_20005  Zip_20015  Zip_20019   Zip_20052  Zip_20001
50  Zip_20059    Zip_20036  Zip_20016  Zip_20003   Zip_20006  Zip_20006
```

We can see that most of the important features are zip code. We can notice that people live in area with zip code 20003 are more likely to register for Democratic and less likely to register for Green. People live in area with zip code 20006 are more likely to register for Non-Partisan and less likely to register for Libertarian or Other. People live in area with zip code 20003 are more likely to register for Democratic and less likely to register for Green. People live in area with zip code 20059 are more likely to register for Libertarian and Other and less likely to register for Democratic.

Different parties can do more propaganda in area with different zip code shown above.

Although location seems to play an important role, we also want to explore how important the other features are.

[427]:
```
DC_tmp_1 = []
for i in DC_party_names:
    coefsDF.sort_values(i, ascending=False, inplace=True)
    tmp = []
    for j in np.array(coefsDF.name):
        if 'Zip' not in j:
            tmp.append(j)
    DC_tmp_1.append(tmp)
```

[428]:
```
DC_tmp_1 = pd.DataFrame(np.transpose(DC_tmp_1))
DC_tmp_1.columns = DC_party_names
DC_tmp_1.head()
```

[428]:
```
                           Democratic                      Non-Partisan  \
0    Ethnicity_Likely Af-Am (Modeled)                  Religion_Islamic   
1                    Religion_Islamic                Ethnicity_Hispanic   
2  Home_Owner_Or_Renter_Likely Renter  Ethnicity_Likely Af-Am (Modeled)   
3                  Ethnicity_Hispanic                  Ethnicity_German   
4        Home_Owner_Or_Renter_Unknown                   Ethnicity_Other   

              Republican                   Green                Libertarian  \
```

```
0  Marital_Status_Married     Religion_Islamic             EGame_Interest_No
1                 Gender_F       Religion_Other                      Gender_M
2          Religion_Jewish  Religion_Protestant              Religion_Unknown
3        Religion_Catholic         Gun_Owner_No                      Gender_F
4                 Gender_M             Gender_M  Marital_Status_Not Married

                        Other
0            Religion_Islamic
1  Marital_Status_Not Married
2              Religion_Other
3           EGame_Interest_No
4      Marital_Status_Married
```

[429]:
```
DC_tmp_1.tail(5)
```

[429]:
```
                    Democratic              Non-Partisan  \
17                    Gender_M  Interest_in_shooting_No
18      Marital_Status_Married         Religion_Catholic
19           Religion_Catholic                  Gender_M
20  Marital_Status_Not Married                  Gender_F
21           EGame_Interest_No    Marital_Status_Married

                            Republican                       Green  \
17  Home_Owner_Or_Renter_Likely Renter            Ethnicity_German
18                  Ethnicity_Hispanic      Marital_Status_Married
19                        Gun_Owner_No            Religion_Unknown
20    Ethnicity_Likely Af-Am (Modeled)             Religion_Jewish
21                    Religion_Islamic  Marital_Status_Not Married

                           Libertarian                               Other
17  Home_Owner_Or_Renter_Likely Renter        Home_Owner_Or_Renter_Unknown
18                 Religion_Protestant                            Gender_M
19    Ethnicity_Likely Af-Am (Modeled)  Home_Owner_Or_Renter_Likely Renter
20                      Religion_Other                            Gender_F
21                    Religion_Islamic                    Ethnicity_German
```

After dropping all the location information, we can notice that people with religion Islamic are more likely to register for Democratic, Non-Partisan, Green, and Other, and they are less likely to register for Republican and Libertarian. People with ethnicity Hispanic are more likely to register for Non-Partisan and less likely to register for Republican. Married people are more likely to register for Republican and less likely to register for Non-Partisan.

From the above result, the party Democratic should do more propaganda to people who are not interested in EGame, who are not married, and with religion Catholic. The party Non-Partisan should do more propaganda to people who are married and with religion Catholic. The party Republican should do more propaganda to people with religion Islamic, with ethnicity Likely Af-Am (Modeled), and who do not have a gun. The party Green should do more propaganda to people who are not married, with religion Jewish, and unknown religion. The party Libertarian should do more propaganda to people with religion Islamicm, ethnicity Likely Af-Am (Modeled), and with protestant. Other parties should do more propaganda to people with ethnicity German, female, and are likely to be a renter.

2.1.2 Alaska

In the logistic regression, we will tune elasticNetParam with values 0, 0.5, 1, and regParam with values 0, 0.1, 0.5.

[430]:
```
# build ParamGrid
lr_params = ParamGridBuilder() \
  .addGrid(lr.elasticNetParam, [0, 0.5, 1]) \
  .addGrid(lr.regParam, [0, 0.1, 0.5]) \
  .build()
# build cross validator model
lr_cv = CrossValidator(estimator=lr, estimatorParamMaps=lr_params,␣
 ↪evaluator=evaluator, numFolds=3, seed=23)
```

[ ]:
```
AK_lr_cv = lr_cv.fit(AK_train)  # fit the model on the training set
```

[ ]:
```
AK_lr_cv.save('gs://final-proj-135/notebooks/jupyter/AK_lr_cv')   # save the␣
 ↪model
```

[456]:
```
lr_model = CrossValidatorModel.load('gs://final-proj-135/notebooks/jupyter/
 ↪AK_lr_cv')  # load the model
```

[433]:
```
fittedTest = lr_model.transform(AK_test)  # fit the model on testing set
```

[434]:
```
print('accuracy: '+ str(evaluator.evaluate(fittedTest, {evaluator.metricName:␣
 ↪"accuracy"})))
print('f1: '+ str(evaluator.evaluate(fittedTest, {evaluator.metricName: "f1"})))
```

```
accuracy: 0.3399460708782743
```

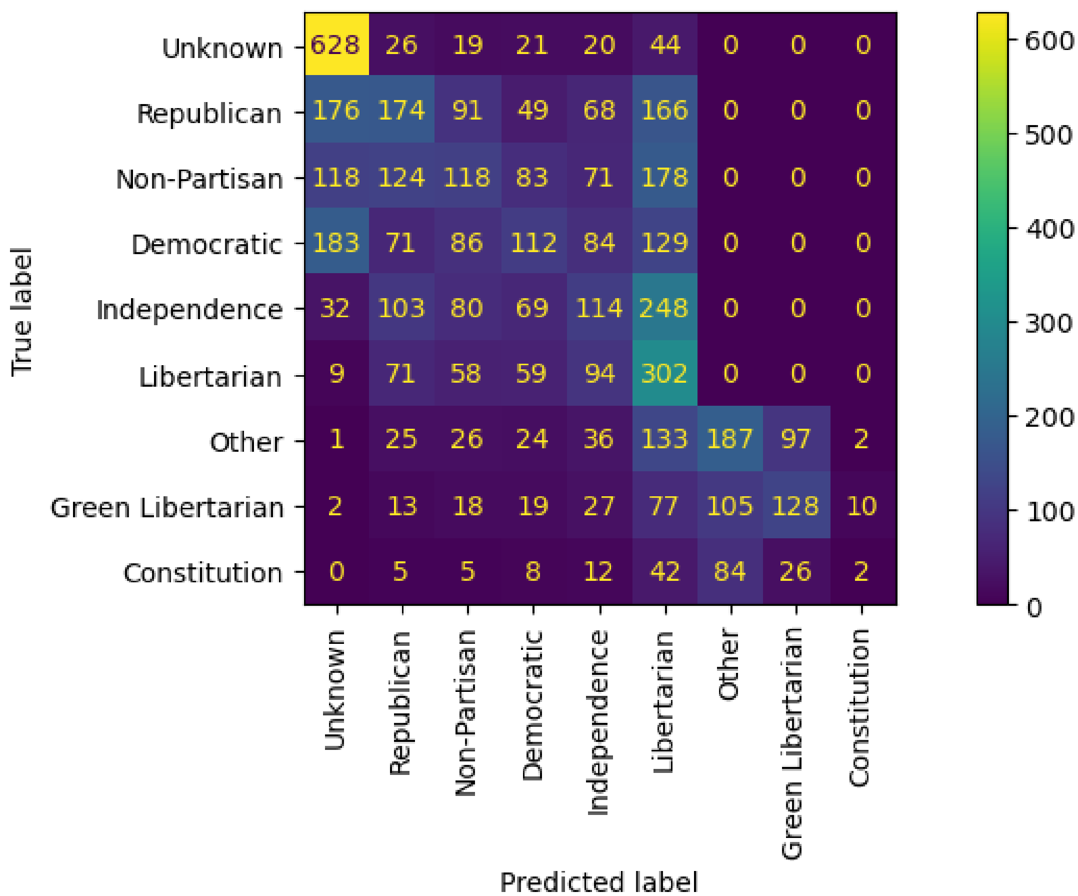
```
f1: 0.3181541008790671
```

After cross validation, the best f1 score for logistic regression in Alaska is around 0.3182 and the accuracy is around 0.3399. This is not that bad since we are classifying 9 parties. Now we plot the confusion matrix.

[435]:
```
y_true = fittedTest.select(['label']).collect()
y_pred = fittedTest.select(['prediction']).collect()
```

```
[436]: AK_party_names =␣
        ↪['Unknown','Republican','Non-Partisan','Democratic','Independence','Libertarian','Other',
                       'Green Libertarian','Constitution']
       cm = confusion_matrix(y_true, y_pred)
       disp = ConfusionMatrixDisplay(confusion_matrix=cm,␣
        ↪display_labels=AK_party_names)
       disp.plot(xticks_rotation='vertical')
```

```
[436]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
       0x7f55998b32b0>
```



From the confusion matrix, we can notice that the number on the diagonal is the largest in each column except for the party Constitution. This is probably because the training data for Constitution is much less than the other parties. But the model is still classifying between different parties.

```
[437]: print(classification_report(y_true, y_pred))
```

```
              precision    recall  f1-score   support
```

```
         0.0       0.55      0.83      0.66       758
         1.0       0.28      0.24      0.26       724
         2.0       0.24      0.17      0.20       692
         3.0       0.25      0.17      0.20       665
         4.0       0.22      0.18      0.19       646
         5.0       0.23      0.51      0.32       593
         6.0       0.50      0.35      0.41       531
         7.0       0.51      0.32      0.39       399
         8.0       0.14      0.01      0.02       184

    accuracy                           0.34      5192
   macro avg       0.32      0.31      0.30      5192
weighted avg       0.33      0.34      0.32      5192
```

We can see that the f1 scores for Unknown is the highest, and for Other and Green Libertarian are relatively high, which means the model can classify these three parties better. The f1 scores for Constitution is muche lower. This is probobaly because the data from this party that are used to train the model is less than those of the other parties.

[438]:
```
print(lr_model.bestModel.explainParams().split('\n')[1]) # elasticNetParam
print(lr_model.bestModel.explainParams().split('\n')[13]) # regParam
```

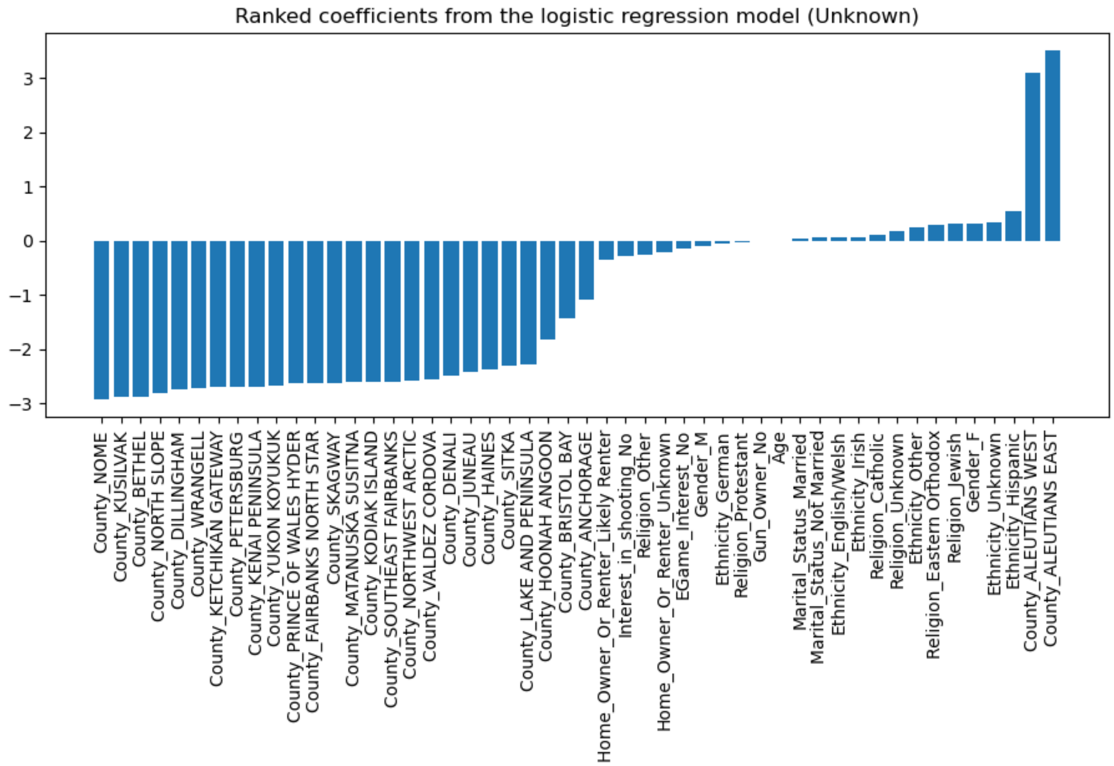
```
elasticNetParam: the ElasticNet mixing parameter, in range [0, 1]. For alpha =
0, the penalty is an L2 penalty. For alpha = 1, it is an L1 penalty. (default:
0.0, current: 0.0)
regParam: regularization parameter (>= 0). (default: 0.0, current: 0.0)
```

After cross validation, the best model has elasticNetParam=0 and regParam=0.

Now, we are going to analyze the feature importance in this logistic regression model.

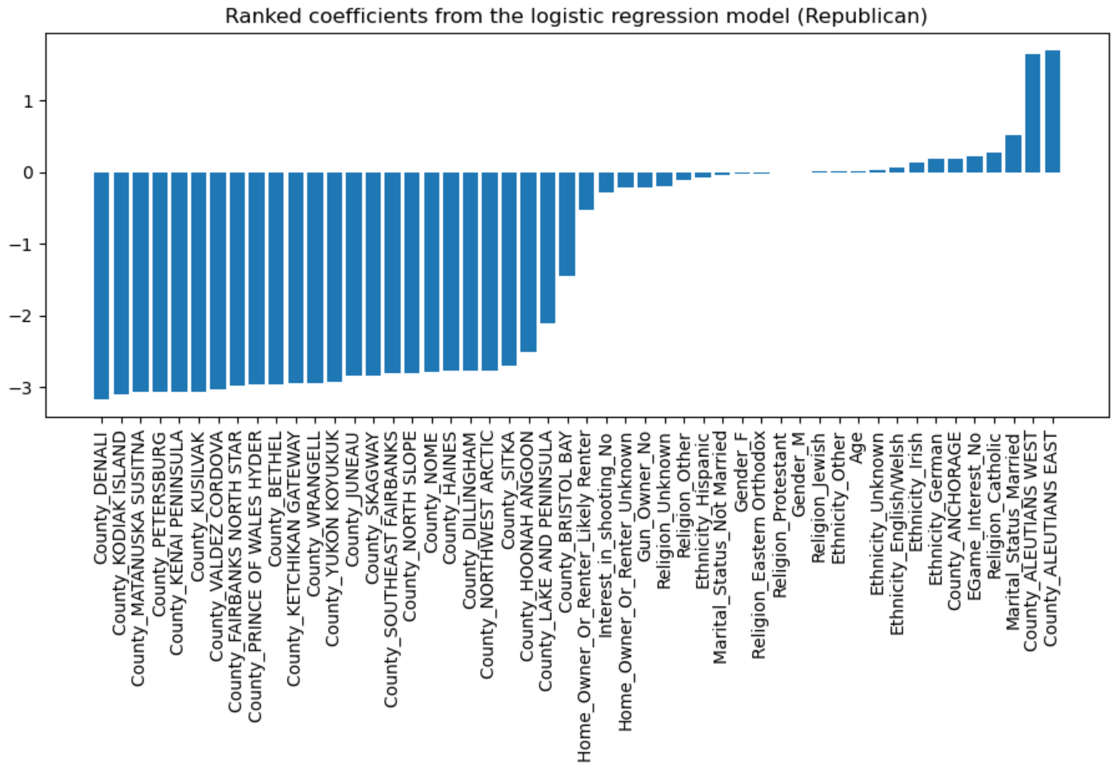
[439]:
```
coefsArray = lr_model.bestModel.coefficientMatrix.toArray() # convert to np.
 ↪array
coefsDF = pd.DataFrame(coefsArray.transpose(), columns=AK_party_names) # to␣
 ↪pandas
coefsDF = coefsDF.merge(AK_featureCols, left_index=True, right_index=True)
```

[440]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Unknown', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Unknown'])
plt.title('Ranked coefficients from the logistic regression model (Unknown)')
plt.show()
```



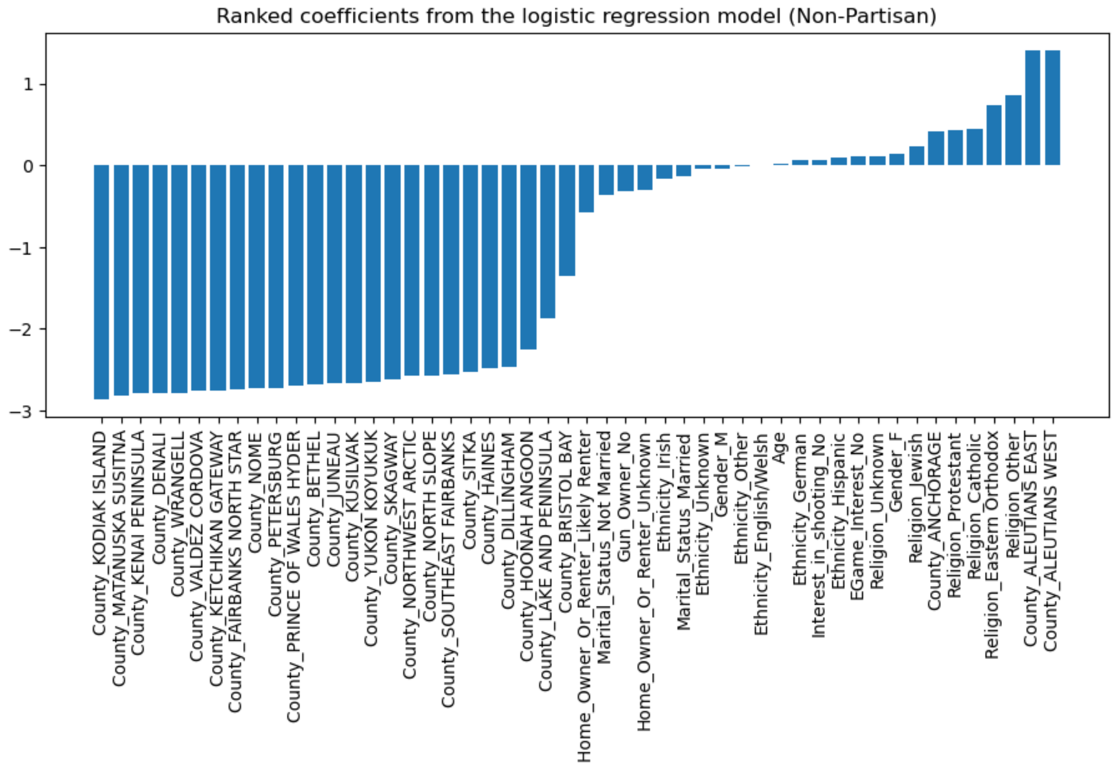
We can see that people who live in the county Aleutians east, Aleutians west, and with ethnicity Hispanic are more likely to register for Unknown parties. People who live in the county Noma, Kusilvak, and Bethel are less likely to register for Unknown parties.

[441]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Republican', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Republican'])
plt.title('Ranked coefficients from the logistic regression model (Republican)')
plt.show()
```



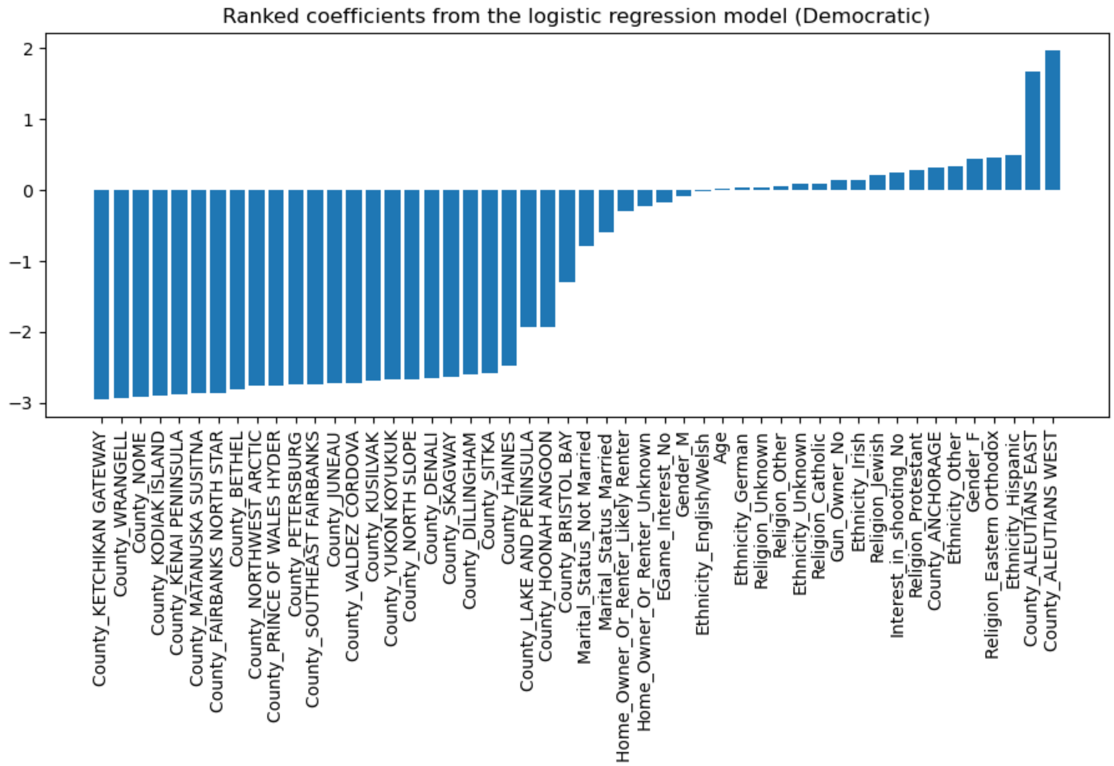
We can see that people who live in the county Aleutians east, Aleutians west, and with married marital status are more likely to register for Republican. People who live in the county Denali, Kodiak island, and Matanuska Susitna are less likely to register for Republican.

[442]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Non-Partisan', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Non-Partisan'])
plt.title('Ranked coefficients from the logistic regression model␣
↪(Non-Partisan)')
plt.show()
```



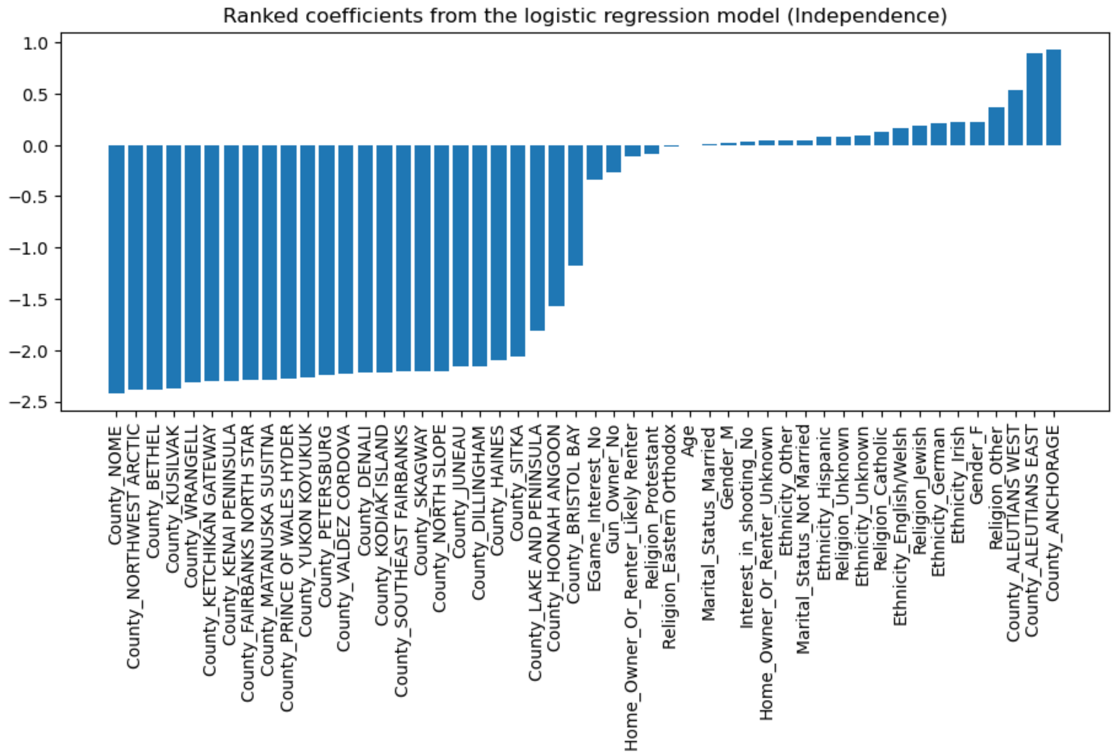
We can see that people who live in the county Aleutians east, Aleutians west, and with religion other than the top five religions in Alaska are more likely to register for Non-Partisan. People who live in the county Kodiak island, Matanuska susitna, and Kenal peninsula are less likely to register for Non-Partisan.

[443]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Democratic', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Democratic'])
plt.title('Ranked coefficients from the logistic regression model (Democratic)')
plt.show()
```



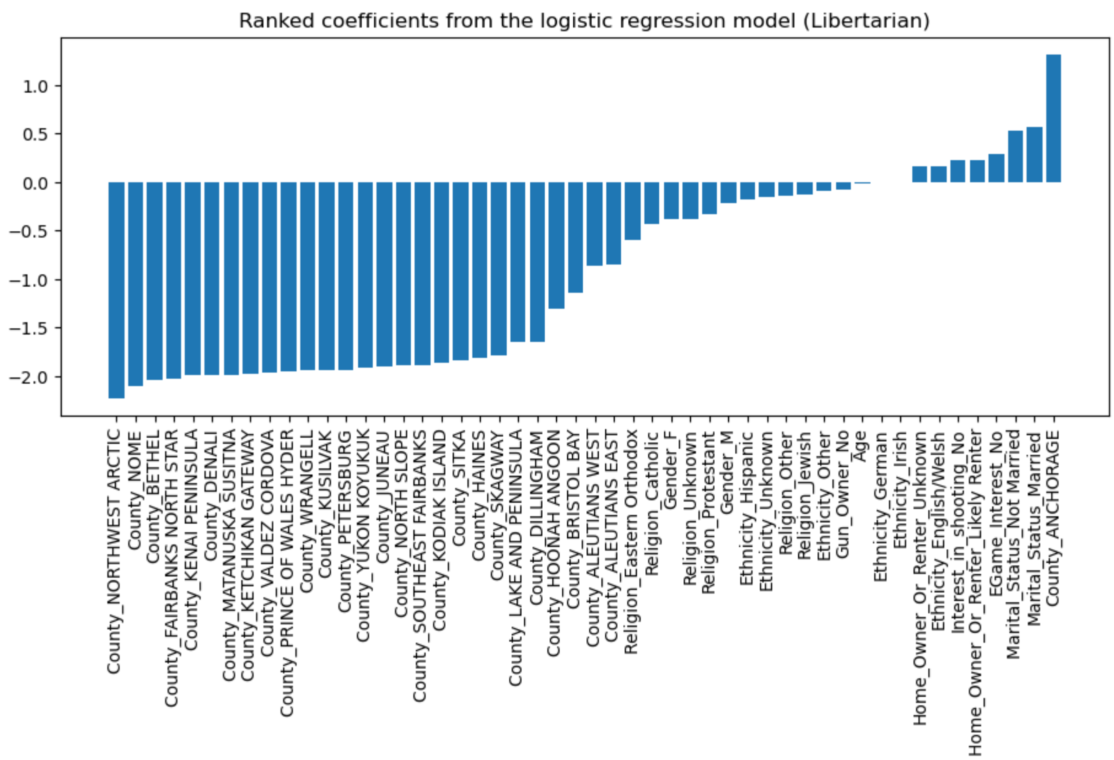
We can see that people who live in the county Aleutians east, Aleutians west, and with ethnicity Hispanic are more likely to register for Democratic. People who live in the county Ketchikan gateway, Wrangell, and Nome are less likely to register for Democratic.

[444]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Independence', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Independence'])
plt.title('Ranked coefficients from the logistic regression model␣
↪(Independence)')
plt.show()
```



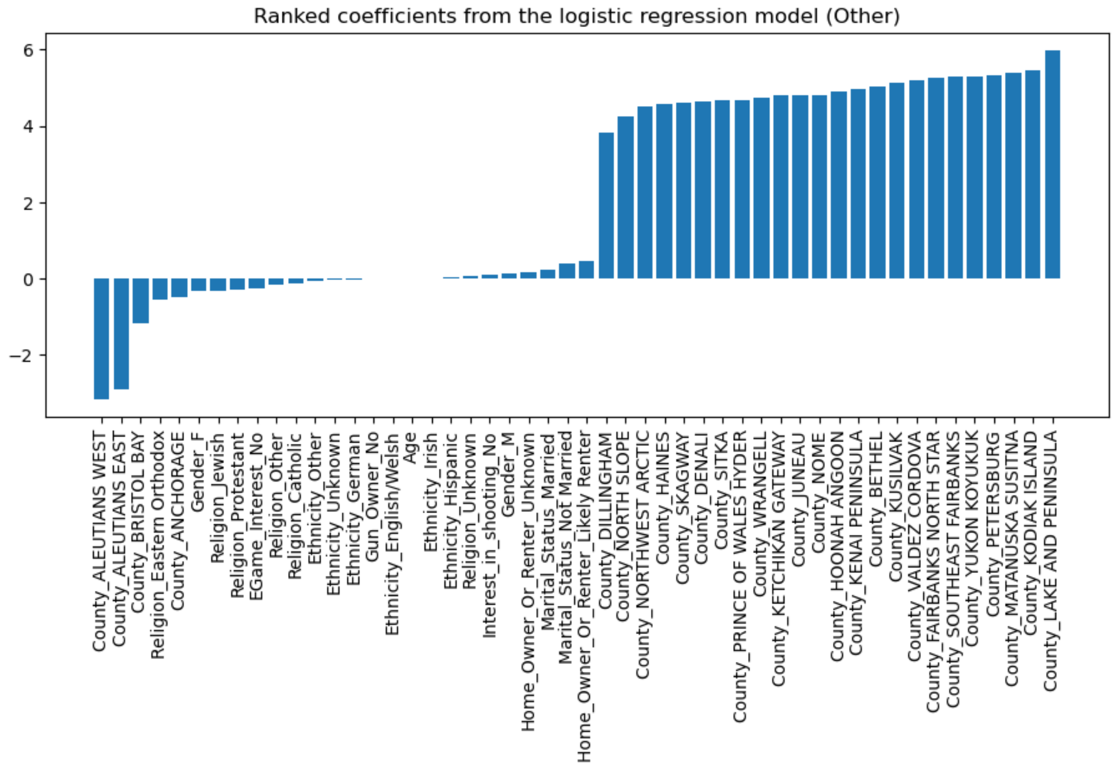
We can see that people who live in the county Anchorage, Aleutians west, and Aleutians east are more likely to register for Independence. People who live in the county Nome, Northwest arctic, and Bethel are less likely to register for Independence.

[445]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Libertarian', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Libertarian'])
plt.title('Ranked coefficients from the logistic regression model␣
 ↪(Libertarian)')
plt.show()
```



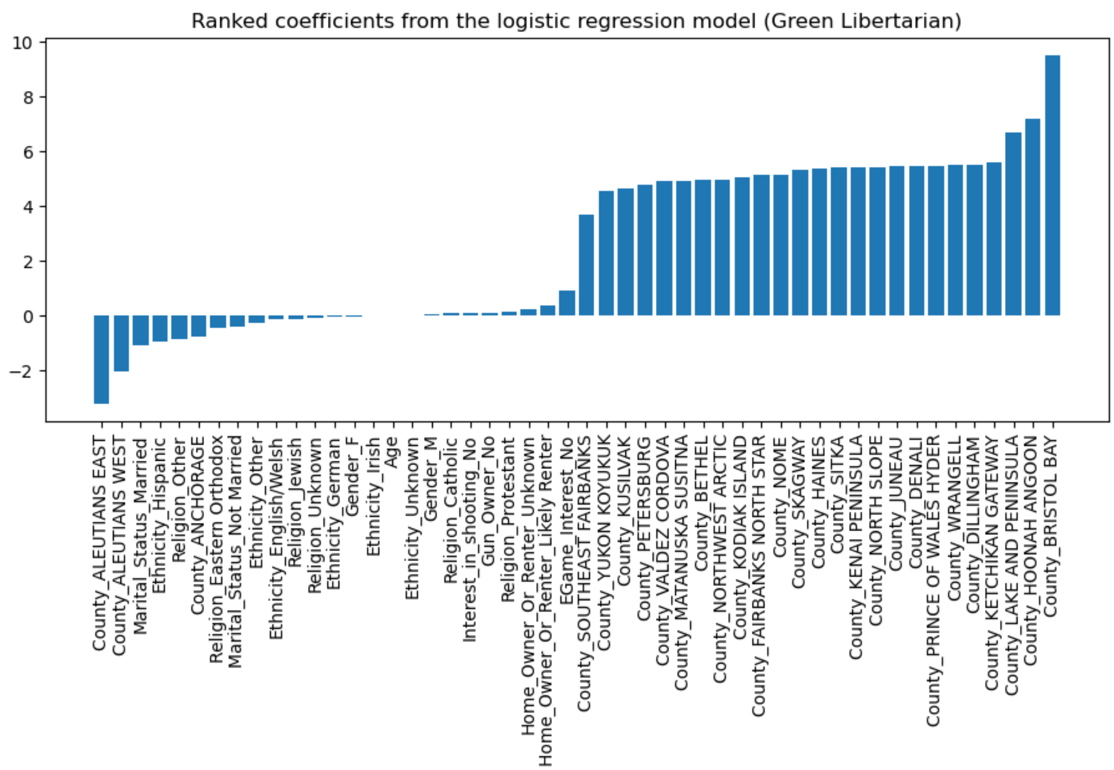
We can see that people who live in the county Anchorage, who are married, and who do not have interest in EGame are more likely to register for Libertarian. People who live in the county Northwest arctic, Nome, and Bethel are less likely to register for Libertarian.

[446]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Other', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Other'])
plt.title('Ranked coefficients from the logistic regression model (Other)')
plt.show()
```



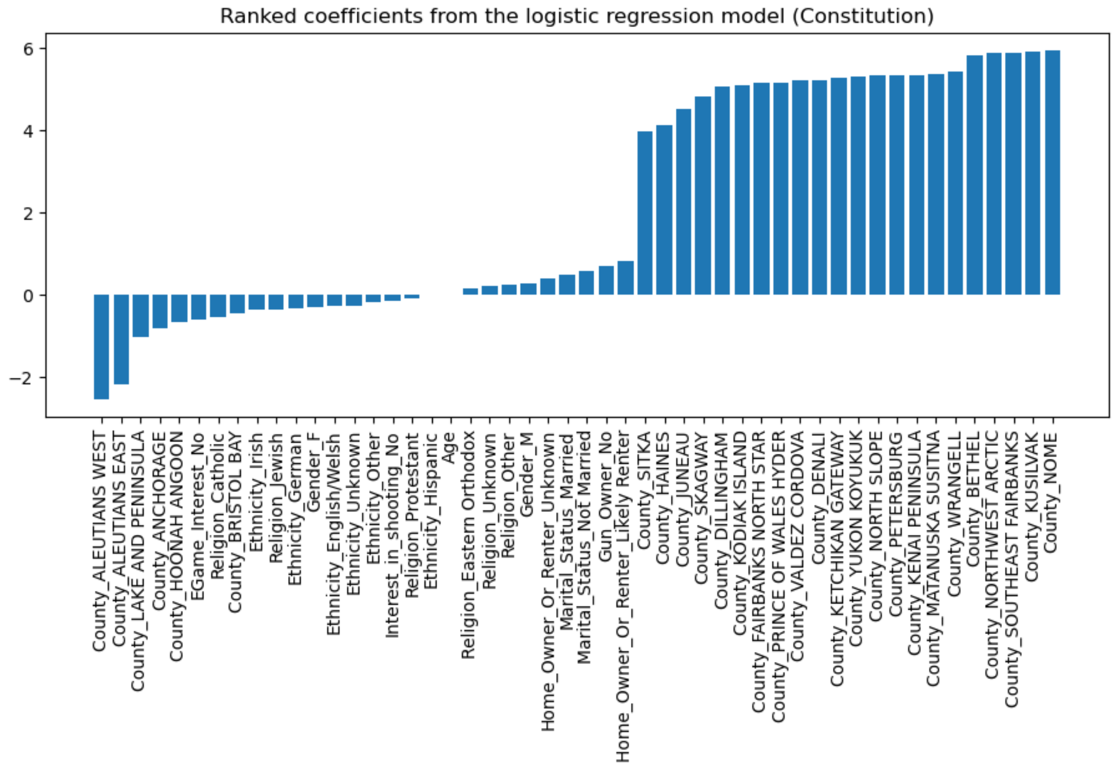
We can see that people who live in the county Lake and peninsula, Kodiak island, and Matanuska susitna are more likely to register for Other. People who live in the county Aleutians west, Aleutians east, and Bristol bay are less likely to register for Other.

```
[447]: plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Green Libertarian', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Green Libertarian'])
plt.title('Ranked coefficients from the logistic regression model (Green␣
↪Libertarian)')
plt.show()
```



We can see that people who live in the county Bristol bay, Hoonah Angoon, and Lake and peninsula are more likely to register for Green Libertarian. People who live in the county Aleutians east, Aleutians west, and who are married are less likely to register for Green Libertarian.

[448]:
```
plt.rcParams["figure.figsize"] = (11,4)
coefsDF.sort_values('Constitution', inplace=True)
plt.xticks(rotation=90)
plt.bar(coefsDF.name, coefsDF['Constitution'])
plt.title('Ranked coefficients from the logistic regression model␣
↪(Constitution)')
plt.show()
```



We can see that people who live in the county Nome, Kusilvak, and Southerneast fairbanks are more likely to register for Constitution. People who live in the county Aleutians west, Aleutians east, and Lake and peninsula are less likely to register for Constitution.

We now list the feature importance for different parties into table.

[449]:
```python
AK_tmp = []
for i in AK_party_names:
    coefsDF.sort_values(i, ascending=False, inplace=True)
    AK_tmp.append(np.array(coefsDF.name))
```

[450]:
```python
AK_tmp = pd.DataFrame(np.transpose(AK_tmp))
AK_tmp.columns = AK_party_names
AK_tmp.head()
```

[450]:
```
                 Unknown              Republican               Non-Partisan  \
0  County_ALEUTIANS EAST   County_ALEUTIANS EAST      County_ALEUTIANS WEST
1  County_ALEUTIANS WEST   County_ALEUTIANS WEST      County_ALEUTIANS EAST
2     Ethnicity_Hispanic  Marital_Status_Married             Religion_Other
3      Ethnicity_Unknown       Religion_Catholic  Religion_Eastern Orthodox
4               Gender_F       EGame_Interest_No          Religion_Catholic

                   Democratic            Independence  \
```

```
0      County_ALEUTIANS WEST       County_ANCHORAGE
1      County_ALEUTIANS EAST  County_ALEUTIANS EAST
2         Ethnicity_Hispanic  County_ALEUTIANS WEST
3  Religion_Eastern Orthodox         Religion_Other
4                   Gender_F               Gender_F

                        Libertarian                     Other  \
0                  County_ANCHORAGE  County_LAKE AND PENINSULA
1              Marital_Status_Married       County_KODIAK ISLAND
2          Marital_Status_Not Married   County_MATANUSKA SUSITNA
3                   EGame_Interest_No         County_PETERSBURG
4  Home_Owner_Or_Renter_Likely Renter       County_YUKON KOYUKUK

         Green Libertarian                Constitution
0         County_BRISTOL BAY                 County_NOME
1       County_HOONAH ANGOON             County_KUSILVAK
2  County_LAKE AND PENINSULA  County_SOUTHEAST FAIRBANKS
3   County_KETCHIKAN GATEWAY     County_NORTHWEST ARCTIC
4          County_DILLINGHAM               County_BETHEL
```

[451]:
```
AK_tmp.tail()
```

[451]:
```
              Unknown                Republican             Non-Partisan  \
45   County_DILLINGHAM    County_KENAI PENINSULA             County_WRANGELL
46  County_NORTH SLOPE         County_PETERSBURG             County_DENALI
47       County_BETHEL  County_MATANUSKA SUSITNA    County_KENAI PENINSULA
48     County_KUSILVAK      County_KODIAK ISLAND  County_MATANUSKA SUSITNA
49         County_NOME             County_DENALI      County_KODIAK ISLAND

                   Democratic             Independence  \
45     County_KENAI PENINSULA          County_WRANGELL
46       County_KODIAK ISLAND          County_KUSILVAK
47                County_NOME            County_BETHEL
48            County_WRANGELL  County_NORTHWEST ARCTIC
49  County_KETCHIKAN GATEWAY              County_NOME

                    Libertarian                      Other  \
45        County_KENAI PENINSULA           County_ANCHORAGE
46  County_FAIRBANKS NORTH STAR  Religion_Eastern Orthodox
47                 County_BETHEL         County_BRISTOL BAY
48                   County_NOME      County_ALEUTIANS EAST
49      County_NORTHWEST ARCTIC      County_ALEUTIANS WEST

         Green Libertarian               Constitution
45          Religion_Other        County_HOONAH ANGOON
46       Ethnicity_Hispanic            County_ANCHORAGE
47  Marital_Status_Married  County_LAKE AND PENINSULA
```

```
48   County_ALEUTIANS WEST      County_ALEUTIANS EAST
49   County_ALEUTIANS EAST      County_ALEUTIANS WEST
```

We can see that most of the important features are information of County. We can notice that people who live in Aleutians east and Aleutians west are more likely to register for Unknown parties, Republican, Non-Partisan, Democratic, and Independence, and they are less likely to register for Other, Green Libertarian, and Constitution. People who live in the county Nome are more likely to register for Constitution, but they are less likely to register for Unknown parties, Independence, and Libertarian.

Different parties can do more propaganda in different counties shown above.

Although location seems to play an important role, we also want to explore how important the other features are.

[452]:
```
AK_tmp_1 = []
for i in AK_party_names:
    coefsDF.sort_values(i, ascending=False, inplace=True)
    tmp = []
    for j in np.array(coefsDF.name):
        if 'County' not in j:
            tmp.append(j)
    AK_tmp_1.append(tmp)
```

[453]:
```
AK_tmp_1 = pd.DataFrame(np.transpose(AK_tmp_1))
AK_tmp_1.columns = AK_party_names
AK_tmp_1.head()
```

[453]:
```
                     Unknown              Republican  \
0         Ethnicity_Hispanic  Marital_Status_Married
1          Ethnicity_Unknown       Religion_Catholic
2                   Gender_F       EGame_Interest_No
3            Religion_Jewish        Ethnicity_German
4  Religion_Eastern Orthodox         Ethnicity_Irish

                Non-Partisan                 Democratic      Independence  \
0             Religion_Other         Ethnicity_Hispanic    Religion_Other
1  Religion_Eastern Orthodox  Religion_Eastern Orthodox          Gender_F
2          Religion_Catholic                   Gender_F   Ethnicity_Irish
3        Religion_Protestant            Ethnicity_Other  Ethnicity_German
4            Religion_Jewish        Religion_Protestant   Religion_Jewish

                          Libertarian                              Other  \
0              Marital_Status_Married  Home_Owner_Or_Renter_Likely Renter
1          Marital_Status_Not Married          Marital_Status_Not Married
2                   EGame_Interest_No              Marital_Status_Married
3  Home_Owner_Or_Renter_Likely Renter        Home_Owner_Or_Renter_Unknown
4               Interest_in_shooting_No                            Gender_M
```

```
                   Green Libertarian                         Constitution
0                  EGame_Interest_No  Home_Owner_Or_Renter_Likely Renter
1  Home_Owner_Or_Renter_Likely Renter                        Gun_Owner_No
2        Home_Owner_Or_Renter_Unknown          Marital_Status_Not Married
3                Religion_Protestant              Marital_Status_Married
4                       Gun_Owner_No        Home_Owner_Or_Renter_Unknown
```

[454]:
```
AK_tmp_1.tail()
```

[454]:
```
                               Unknown                          Republican  \
17                   EGame_Interest_No                    Religion_Unknown
18        Home_Owner_Or_Renter_Unknown                        Gun_Owner_No
19                      Religion_Other        Home_Owner_Or_Renter_Unknown
20             Interest_in_shooting_No             Interest_in_shooting_No
21  Home_Owner_Or_Renter_Likely Renter  Home_Owner_Or_Renter_Likely Renter

                          Non-Partisan                          Democratic  \
17                     Ethnicity_Irish                   EGame_Interest_No
18        Home_Owner_Or_Renter_Unknown        Home_Owner_Or_Renter_Unknown
19                        Gun_Owner_No  Home_Owner_Or_Renter_Likely Renter
20          Marital_Status_Not Married              Marital_Status_Married
21  Home_Owner_Or_Renter_Likely Renter          Marital_Status_Not Married

                          Independence              Libertarian  \
17          Religion_Eastern Orthodox       Religion_Protestant
18                 Religion_Protestant         Religion_Unknown
19  Home_Owner_Or_Renter_Likely Renter                Gender_F
20                        Gun_Owner_No        Religion_Catholic
21                   EGame_Interest_No  Religion_Eastern Orthodox

                        Other           Green Libertarian       Constitution
17          EGame_Interest_No  Marital_Status_Not Married   Ethnicity_German
18        Religion_Protestant   Religion_Eastern Orthodox    Religion_Jewish
19            Religion_Jewish              Religion_Other    Ethnicity_Irish
20                   Gender_F          Ethnicity_Hispanic  Religion_Catholic
21  Religion_Eastern Orthodox      Marital_Status_Married  EGame_Interest_No
```

After dropping all the location information, we can notice that people with ethnicity Hispanic are more likely to register for Unknown parties and Democratic, and they are less likely to register for Green Libertarian. People with religions other than the top five religions in Alaska are more likely to register for Non-Partisan and Independence, and they are less likely to register for Unknown parties and Green Libertarian. Female are more likely to register for Unknown parties, Democratic, and Independence, and they are less likely to register for Libertarian and Other. People with religion Catholic are more likely to register for Republican and Non-Partisan, and they are less likely to register for Libertarian and Constitution.

From the above result, the party Republican should do more propaganda to people who are likely to be a renter, who do not have interest in shooting, and who do not have a gun. The party Non-Partisan should do more propaganda to people who are likely to be a renter, who are not married, and with ethnicity Irish. The party Democratic should do more propaganda to people who are not married, who are likely to be a renter, and who do not have interest in EGame. The party Independence should do more propaganda to people who do not have interest in EGame or gun, who are likely to be a renter, and with religions Protestant and Eastern Orthodox. The party Libertarian should do more propaganda to people with religion Eastern Orthodox, Catholic, and Protestant, and female. The Other parties should do more propaganda to people with religion Eastern Orthodox, Jewish, and Protestant, and female. The party Green Libertarian should do more propaganda to people who are married, who with ethnicity Hispanic, and with religion other than top five religions in Alaska. The party Constitution should do more propaganda to people who do not have intterest in EGame, with religion Catholic and Jewish, and ethnicity Irish and German.

2.1.3 Decision Tree

2.1.4 WASHINGTON D.C.

[301]:
```
dt_params = ParamGridBuilder() \
  .addGrid(dt.maxDepth, [5, 10, 15]) \
  .build()

dt_cv = CrossValidator(estimator=dt, estimatorParamMaps=dt_params,␣
 ↪evaluator=evaluator, numFolds=3, seed=33)
```

[302]:
```
DC_dt_cv = dt_cv.fit(DC_train)
```

[303]:
```
fittedTest_dt_DC = DC_dt_cv.transform(DC_test)
```

[304]:
```
print('accuracy: '+ str(evaluator.evaluate(fittedTest_dt_DC, {evaluator.
 ↪metricName: "accuracy"})))
print('f1: '+ str(evaluator.evaluate(fittedTest_dt_DC, {evaluator.metricName:␣
 ↪"f1"})))
```

```
accuracy: 0.5087201502548967
[Stage 25619:================================================>        (6 + 1) / 7]
f1: 0.4847674587841405
```

After calculating the cross validator for the Washington D.C. model, we can see the accuracy is around 50.87% and the f1 values is around 48.48%. Although it seems low, there are 6 different labels being classified so it makes sense for it to be lower than usual.

[305]:

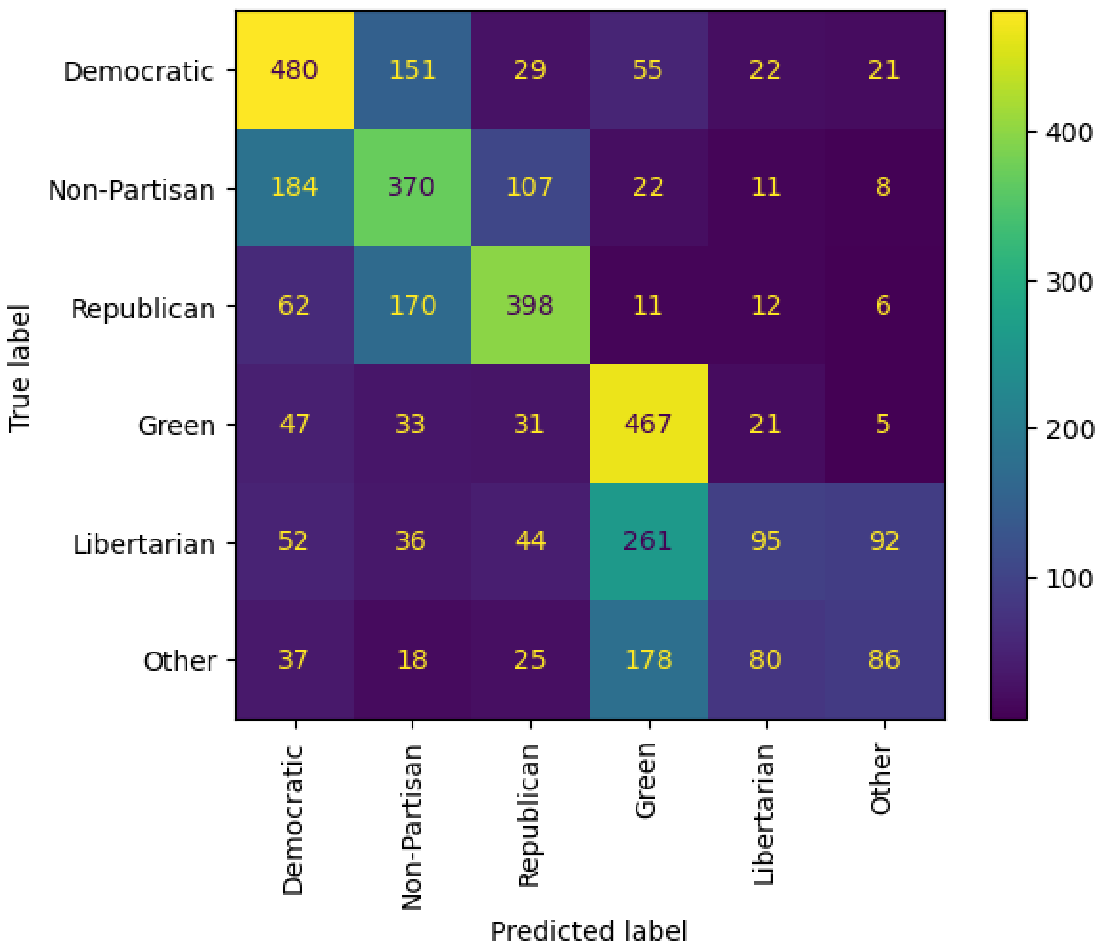
```
y_true_dt = fittedTest_dt_DC.select(['label']).collect()
y_pred_dt = fittedTest_dt_DC.select(['prediction']).collect()
```

[306]:

```
party_names =␣
 ↪['Democratic','Non-Partisan','Republican','Green','Libertarian','Other']
cm = confusion_matrix(y_true_dt, y_pred_dt)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=party_names)
disp.plot(xticks_rotation='vertical')
```

[306]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f558a0e7610>
```



The model mostly did well on its accuracy and performance. For Democratic, Non-Partisan, Republican, and Green, they have the highest values in their true predictions. However, the model seems to label Libertarian and Other as Green party more often than their respective parties.

[307]:
```
print(classification_report(y_true_dt, y_pred_dt))
```

```
              precision    recall  f1-score   support

         0.0       0.56      0.63      0.59       758
         1.0       0.48      0.53      0.50       702
         2.0       0.63      0.60      0.62       659
         3.0       0.47      0.77      0.58       604
         4.0       0.39      0.16      0.23       580
         5.0       0.39      0.20      0.27       424

    accuracy                           0.51      3727
   macro avg       0.49      0.48      0.47      3727
weighted avg       0.50      0.51      0.48      3727
```

[308]:
```
print(DC_dt_cv.bestModel.explainParams().split('\n')[7])
```

```
maxDepth: Maximum depth of the tree. (>= 0) E.g., depth 0 means 1 leaf node;
depth 1 means 1 internal node + 2 leaf nodes. (default: 5, current: 15)
```

We can see that there is a maximum depth of 15 in our tree model.

[309]:
```
#feature importance
featureImportances = DC_dt_cv.bestModel.featureImportances.toArray()
```

[310]:
```
print("Feature Importances: ", featureImportances)
```

```
Feature Importances:  [0.0199978  0.01135268 0.14156581 0.05571737 0.01215687
0.0136531
 0.00594816 0.00492609 0.00873479 0.01776114 0.01808184 0.00741657
 0.0061894  0.00253527 0.00243522 0.01534165 0.00146989 0.00121523
 0.02728693 0.01076673 0.00217199 0.00547858 0.15461792 0.12043901
 0.0416007  0.10000539 0.00110467 0.         0.0727581  0.
 0.01792488 0.01496531 0.01721991 0.         0.         0.
 0.         0.01462117 0.02337024 0.         0.00067979 0.0089044
 0.00829584 0.         0.01128957 0.         0.         0.
 0.         0.         0.        ]
```

[311]:
```
fittedTest_dt_DC.select('label', 'prediction').distinct().show()

DCfeaturedCols = pd.DataFrame(fittedTest_dt_DC.schema["features"].
 ↪metadata["ml_attr"]["attrs"]["binary"]+
fittedTest_dt_DC.schema["features"].metadata["ml_attr"]["attrs"]["numeric"]).
 ↪sort_values("idx")
DCfeaturedCols = DCfeaturedCols.set_index('idx')
print(np.array(DCfeaturedCols).transpose())
```

```
[Stage 25659:=======>                                                (1 + 1) / 7]

+-----+----------+
|label|prediction|
+-----+----------+
|  0.0|       5.0|
|  0.0|       1.0|
|  0.0|       4.0|
|  0.0|       0.0|
|  0.0|       2.0|
|  0.0|       3.0|
|  1.0|       1.0|
|  1.0|       0.0|
|  1.0|       4.0|
|  1.0|       5.0|
|  1.0|       2.0|
|  1.0|       3.0|
|  2.0|       0.0|
|  2.0|       2.0|
|  2.0|       3.0|
|  2.0|       4.0|
|  2.0|       1.0|
|  2.0|       5.0|
|  3.0|       5.0|
|  3.0|       2.0|
+-----+----------+
only showing top 20 rows

[['Gender_M' 'Gender_F' 'Age' 'Ethnicity_Likely Af-Am (Modeled)'
  'Ethnicity_Other' 'Ethnicity_English/Welsh' 'Ethnicity_Unknown'
  'Ethnicity_Hispanic' 'Ethnicity_German' 'Religion_Unknown'
  'Religion_Protestant' 'Religion_Jewish' 'Religion_Catholic'
  'Religion_Other' 'Religion_Islamic' 'Marital_Status_Not Married'
  'Marital_Status_Married' 'Gun_Owner_No'
  'Home_Owner_Or_Renter_Likely Renter' 'Home_Owner_Or_Renter_Unknown'
  'EGame_Interest_No' 'Interest_in_shooting_No' 'Zip_20001' 'Zip_20037'
  'Zip_20002' 'Zip_20007' 'Zip_20011' 'Zip_20009' 'Zip_20052' 'Zip_20010'
  'Zip_20019' 'Zip_20003' 'Zip_20020' 'Zip_20016' 'Zip_20017' 'Zip_20008'
  'Zip_20018' 'Zip_20032' 'Zip_20006' 'Zip_20012' 'Zip_20015' 'Zip_20036'
  'Zip_20024' 'Zip_20005' 'Zip_20057' 'Zip_20059' 'Zip_20004' 'Zip_20500'
  'Zip_20373' 'Zip_20422' 'Zip_20431']]
```

These were the features used in the Washington D.C. dataset for decision tree.

2.1.5 ALASKA

[312]:
```
AK_dt_cv = dt_cv.fit(AK_train)
```

```
23/03/22 23:39:59 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1004.6 KiB
23/03/22 23:40:22 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1011.7 KiB
```

[313]:
```
fittedTest_dt_AK = AK_dt_cv.transform(AK_test)
```

[314]:
```
print('accuracy: '+ str(evaluator.evaluate(fittedTest_dt_AK, {evaluator.
 ↪metricName: "accuracy"})))
print('f1: '+ str(evaluator.evaluate(fittedTest_dt_AK, {evaluator.metricName:␣
 ↪"f1"})))
```

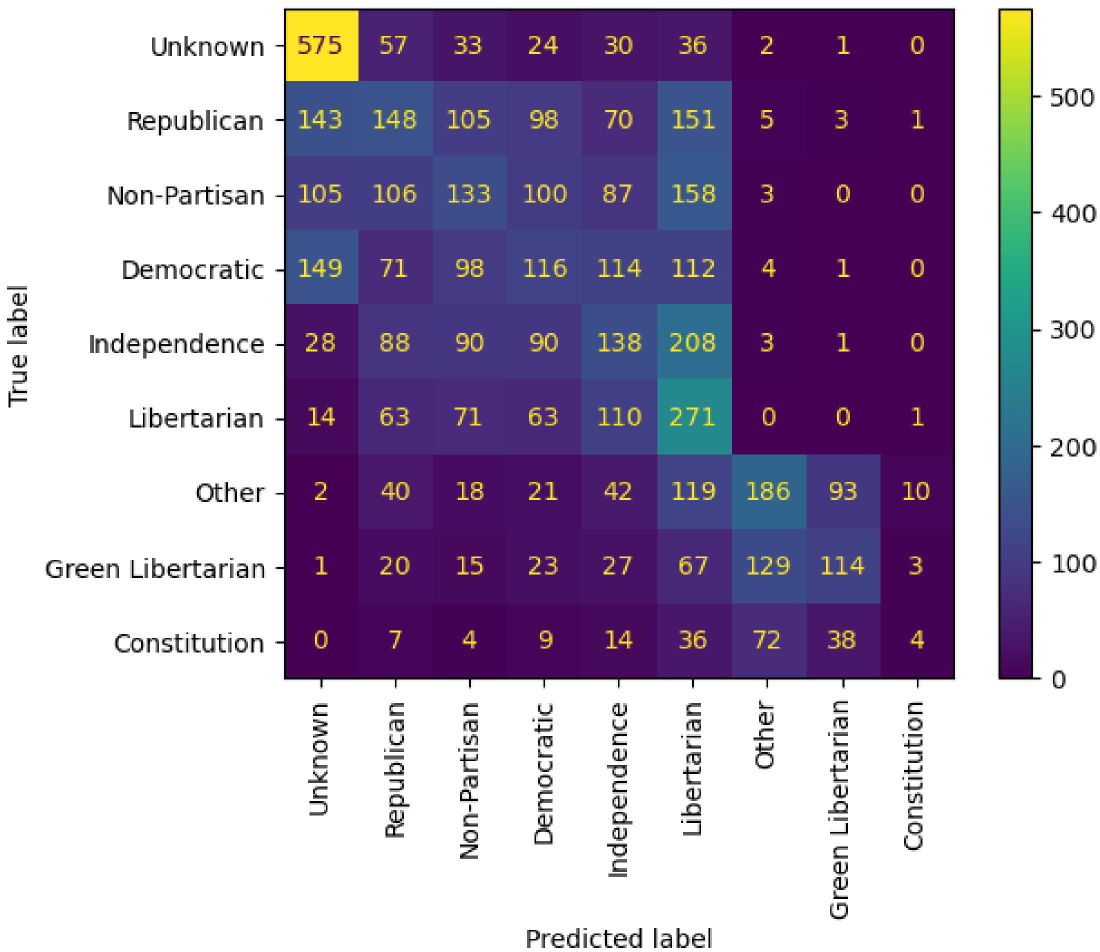
```
accuracy: 0.324537750385208

[Stage 27230:=================================================>      (7 + 1) / 8]

f1: 0.3097676970864137
```

After calculating the cross validator for the Alaska model, we can see the accuracy is around 32.45% and the f1 values is around 30.97%. This is much lower compared to Washington D.C. but in this case, there are 9 different labels being classified as opposed to 6. So a drop in percentage is to be expected.

[315]:
```
y_true_dt = fittedTest_dt_AK.select(['label']).collect()
y_pred_dt = fittedTest_dt_AK.select(['prediction']).collect()
```

[316]:
```
party_names =␣
 ↪['Unknown','Republican','Non-Partisan','Democratic','Independence','Libertarian','Other',
               'Green Libertarian','Constitution']
cm = confusion_matrix(y_true_dt, y_pred_dt)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=party_names)
disp.plot(xticks_rotation='vertical')
```

[316]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f55707a44c0>
```



This is where the classification becomes a little more tricky. There seems to be a a lot more confusion in the model in classifying the parties correctly. Unknown seems to be the most accruately labeled party here. Republicans, Non-Partisan, Democrats, Independent, Green, and Constitution have values in other parties that are not the highest in their own party. Only Libertarian and Other have the highest values in their classification. Most parties are labeled as Libertarian.

[317]:
```
print(classification_report(y_true_dt, y_pred_dt))
```

```
              precision    recall  f1-score   support

         0.0       0.57      0.76      0.65       758
         1.0       0.25      0.20      0.22       724
         2.0       0.23      0.19      0.21       692
         3.0       0.21      0.17      0.19       665
         4.0       0.22      0.21      0.22       646
         5.0       0.23      0.46      0.31       593
         6.0       0.46      0.35      0.40       531
         7.0       0.45      0.29      0.35       399
```

```
         8.0       0.21      0.02      0.04       184

    accuracy                           0.32      5192
   macro avg       0.32      0.30      0.29      5192
weighted avg       0.32      0.32      0.31      5192
```

[318]:
```
print(AK_dt_cv.bestModel.explainParams().split('\n')[7])
```

```
maxDepth: Maximum depth of the tree. (>= 0) E.g., depth 0 means 1 leaf node;
depth 1 means 1 internal node + 2 leaf nodes. (default: 5, current: 10)
```

We can see that there is a maximum depth of 10 in our tree model.

[319]:
```
featureImportances = AK_dt_cv.bestModel.featureImportances.toArray()
```

[320]:
```
print("Feature Importances: ", featureImportances)
```

```
Feature Importances:  [0.02466052 0.00523709 0.14420074 0.02079367 0.01587944
0.00935948
 0.01056436 0.01080246 0.01289925 0.01967566 0.01081237 0.0064723
 0.00222552 0.00388784 0.00454975 0.0156107  0.01042632 0.02123781
 0.0198168  0.01023926 0.00926898 0.02562715 0.24041022 0.10600746
 0.2215137  0.00455875 0.00081576 0.00281592 0.00076453 0.00169413
 0.00082443 0.         0.         0.         0.00271598 0.00063772
 0.         0.0017871  0.         0.00052667 0.         0.
 0.         0.00068017 0.         0.         0.         0.
 0.         0.        ]
```

[321]:
```
fittedTest_dt_AK.select('label', 'prediction').distinct().show()

DCfeaturedCols = pd.DataFrame(fittedTest_dt_AK.schema["features"].
 ↪metadata["ml_attr"]["attrs"]["binary"]+
fittedTest_dt_AK.schema["features"].metadata["ml_attr"]["attrs"]["numeric"]).
 ↪sort_values("idx")
DCfeaturedCols = DCfeaturedCols.set_index('idx')
print(np.array(DCfeaturedCols).transpose())
```

```
[Stage 27298:=================================================>      (8 + 1) / 9]

+-----+----------+
|label|prediction|
+-----+----------+
|  0.0|       5.0|
|  0.0|       1.0|
|  0.0|       4.0|
|  0.0|       6.0|
|  0.0|       7.0|
|  0.0|       0.0|
```

```
|  0.0|       2.0|
|  0.0|       3.0|
|  1.0|       1.0|
|  1.0|       6.0|
|  1.0|       8.0|
|  1.0|       0.0|
|  1.0|       4.0|
|  1.0|       5.0|
|  1.0|       2.0|
|  1.0|       3.0|
|  1.0|       7.0|
|  2.0|       0.0|
|  2.0|       2.0|
|  2.0|       3.0|
+-----+----------+
only showing top 20 rows

[['Gender_M' 'Gender_F' 'Age' 'Ethnicity_English/Welsh' 'Ethnicity_Other'
  'Ethnicity_Unknown' 'Ethnicity_Hispanic' 'Ethnicity_German'
  'Ethnicity_Irish' 'Religion_Unknown' 'Religion_Protestant'
  'Religion_Catholic' 'Religion_Jewish' 'Religion_Eastern Orthodox'
  'Religion_Other' 'Marital_Status_Not Married' 'Marital_Status_Married'
  'Gun_Owner_No' 'Home_Owner_Or_Renter_Likely Renter'
  'Home_Owner_Or_Renter_Unknown' 'EGame_Interest_No'
  'Interest_in_shooting_No' 'County_ANCHORAGE' 'County_ALEUTIANS WEST'
  'County_ALEUTIANS EAST' 'County_MATANUSKA SUSITNA'
  'County_FAIRBANKS NORTH STAR' 'County_KENAI PENINSULA' 'County_JUNEAU'
  'County_BETHEL' 'County_KETCHIKAN GATEWAY' 'County_VALDEZ CORDOVA'
  'County_KODIAK ISLAND' 'County_SITKA' 'County_SOUTHEAST FAIRBANKS'
  'County_NOME' 'County_KUSILVAK' 'County_NORTHWEST ARCTIC'
  'County_PRINCE OF WALES HYDER' 'County_NORTH SLOPE' 'County_HAINES'
  'County_YUKON KOYUKUK' 'County_DENALI' 'County_PETERSBURG'
  'County_SKAGWAY' 'County_HOONAH ANGOON' 'County_WRANGELL'
  'County_DILLINGHAM' 'County_LAKE AND PENINSULA' 'County_BRISTOL BAY']]
```

These were the features used in the Alaska dataset for decision tree.

2.1.6 Random Forest

Washington DC

[322]:
```
rf_params = ParamGridBuilder() \
    .addGrid(rf.maxDepth, [2, 5, 10]) \
    .addGrid(rf.numTrees,[5,20,50]) \
    .build()
```

```
rf_cv = CrossValidator(estimator=rf, estimatorParamMaps=rf_params,␣
↪evaluator=evaluator, numFolds=3, seed=33)
```

[323]:
```
DC_rf_cv = rf_cv.fit(DC_train)
```

```
23/03/22 23:41:51 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1092.4 KiB
23/03/22 23:41:56 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1008.2 KiB
23/03/22 23:41:57 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1350.8 KiB
23/03/22 23:41:59 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1762.2 KiB
23/03/22 23:42:00 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 2.2 MiB
23/03/22 23:42:02 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1422.1 KiB
23/03/22 23:42:31 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1096.6 KiB
23/03/22 23:42:38 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1310.6 KiB
23/03/22 23:42:39 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1704.8 KiB
23/03/22 23:42:40 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 2.1 MiB
23/03/22 23:42:42 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1377.8 KiB
23/03/22 23:43:11 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1100.2 KiB
23/03/22 23:43:18 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1301.3 KiB
23/03/22 23:43:19 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1694.3 KiB
23/03/22 23:43:20 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 2.1 MiB
23/03/22 23:43:22 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1396.8 KiB
23/03/22 23:43:31 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1207.5 KiB
[Stage 29463:=======>                                               (1 + 1) / 7]
```

[324]:
```
fittedTest_rf_DC = DC_rf_cv.transform(DC_test)
```

[325]:
```
print('accuracy: '+ str(evaluator.evaluate(fittedTest_rf_DC, {evaluator.
↪metricName: "accuracy"})))
print('f1: '+ str(evaluator.evaluate(fittedTest_rf_DC, {evaluator.metricName:␣
↪"f1"})))
```

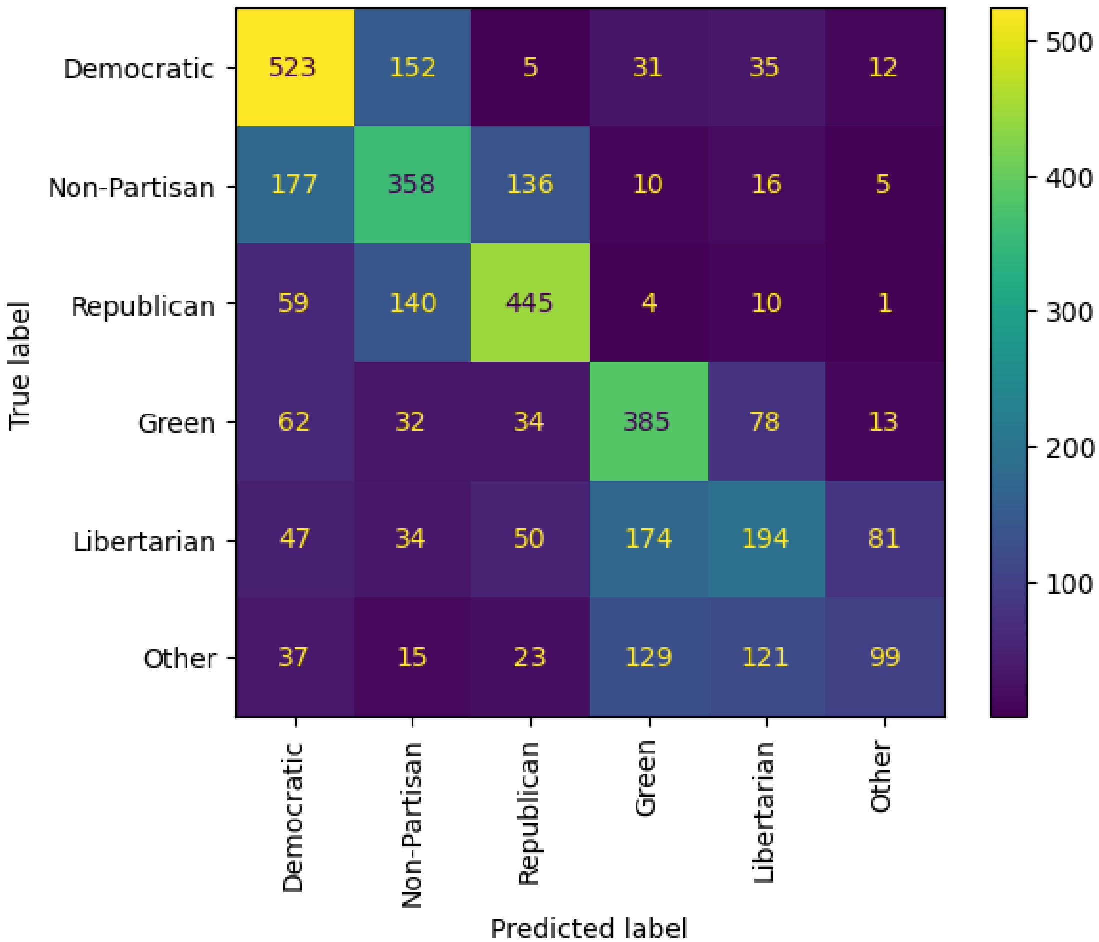
```
accuracy: 0.5376978803327073
[Stage 29483:================================>                        (4 + 1) / 7]
f1: 0.5256333333792581
```

The accuracy of 53.5% and f1 performance of 52.4% are extremely good results, taking into account that we try to classify more than 2 labels

[326]:
```
y_true_rf = fittedTest_rf_DC.select(['label']).collect()
y_pred_rf = fittedTest_rf_DC.select(['prediction']).collect()
```

[327]:
```
party_names =␣
↪['Democratic','Non-Partisan','Republican','Green','Libertarian','Other']
cm = confusion_matrix(y_true_rf, y_pred_rf)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=party_names)
disp.plot(xticks_rotation='vertical')
```

[327]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f558be2f370>
```



The true predictions for each party being the highest value signifies that the model did a good job with fitting the MultiLabel classification

[328]:
```
print(DC_rf_cv.bestModel.explainParams().split('\n')[9])
print('\n ')
print(DC_rf_cv.bestModel.explainParams().split('\n')[14])
```

```
maxDepth: Maximum depth of the tree. (>= 0) E.g., depth 0 means 1 leaf node;
depth 1 means 1 internal node + 2 leaf nodes. (default: 5, current: 10)


numTrees: Number of trees to train (>= 1). (default: 20, current: 20)
```

[329]:
```
print(classification_report(y_true_rf, y_pred_rf))
```

```
              precision    recall  f1-score   support

         0.0       0.58      0.69      0.63       758
```

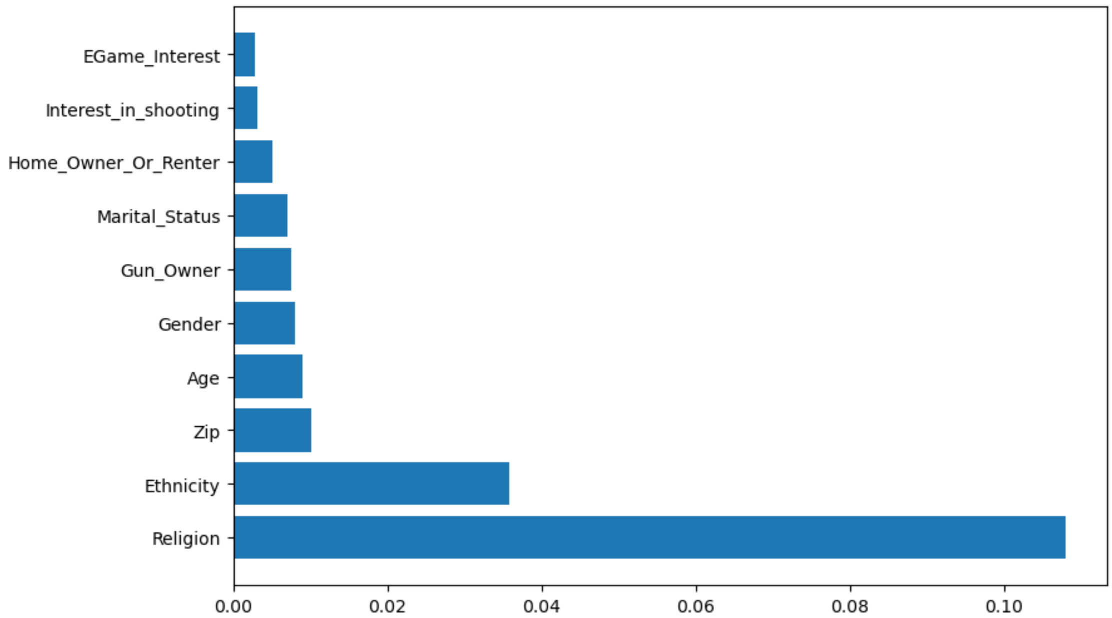
```
         1.0       0.49      0.51      0.50       702
         2.0       0.64      0.68      0.66       659
         3.0       0.53      0.64      0.58       604
         4.0       0.43      0.33      0.38       580
         5.0       0.47      0.23      0.31       424

    accuracy                           0.54      3727
   macro avg       0.52      0.51      0.51      3727
weighted avg       0.53      0.54      0.53      3727
```

From here we can notice that people also majorly vote Democratic and Republican, as in Logistic Regression

[332]:
```
def get_features_importance(dataset= fittedTest_rf_DC, model=DC_rf_cv):
    """
    Careful! this function is hard-coded inside for feature names.
    I created earlier `to_encode` and `numerical_cols` lists for Xs names; I'm␣
 ↪using that here.
    """
    sparse= model.bestModel.featureImportances
    vals= sparse.values
    idx= sparse.indices
    feature_names=dataset.drop('Party','features','label', 'rawPrediction',␣
 ↪'probability', 'prediction').columns
    importances_df= pd.DataFrame(zip(feature_names, vals), columns=["feature",␣
 ↪"value"])
    return importances_df
```

[333]:
```
rfc_importance_df= get_features_importance().
 ↪sort_values(by='value',ascending=False)
rfc_importance_df.head(20)
plt.figure(figsize=(9,6))
plt.barh(rfc_importance_df['feature'][:20],
        rfc_importance_df['value'][:20])
```

[333]: <BarContainer object of 10 artists>



It looks like Religion plays the major role in Party Classification in DC, followed by Ethnicity, Zip, and Age, which is very different from the results shown in Logistic Regression.

Alaska

[334]:
```
rf_params = ParamGridBuilder() \
    .addGrid(rf.maxDepth, [2, 5, 10]) \
    .addGrid(rf.numTrees,[5,20,50]) \
    .build()

rf_cv = CrossValidator(estimator=rf, estimatorParamMaps=rf_params,␣
 ↪evaluator=evaluator, numFolds=3, seed=33)
```

[335]:
```
AK_rf_cv = rf_cv.fit(AK_train)
```

```
23/03/22 23:46:27 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1286.6 KiB
23/03/22 23:46:28 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1671.6 KiB
23/03/22 23:46:30 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1237.7 KiB
23/03/22 23:46:36 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1297.1 KiB
23/03/22 23:46:38 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1862.2 KiB
23/03/22 23:46:40 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 2.5 MiB
23/03/22 23:46:42 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
```

```
large task binary with size 3.4 MiB
23/03/22 23:46:45 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 2.4 MiB
23/03/22 23:47:27 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1307.8 KiB
23/03/22 23:47:28 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1702.2 KiB
23/03/22 23:47:30 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1269.3 KiB
23/03/22 23:47:36 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1296.5 KiB
23/03/22 23:47:38 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1850.8 KiB
23/03/22 23:47:40 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 2.5 MiB
23/03/22 23:47:42 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 3.4 MiB
23/03/22 23:47:45 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 2.4 MiB
23/03/22 23:48:27 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1301.4 KiB
23/03/22 23:48:28 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1697.5 KiB
23/03/22 23:48:30 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1263.1 KiB
23/03/22 23:48:37 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1311.0 KiB
23/03/22 23:48:38 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1868.3 KiB
23/03/22 23:48:40 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 2.5 MiB
23/03/22 23:48:42 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 3.4 MiB
23/03/22 23:48:45 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 2.4 MiB
23/03/22 23:48:58 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1330.1 KiB
23/03/22 23:48:59 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1779.3 KiB
[Stage 32502:===========================>                          (4 + 1) / 8]
```

[336]:
```
fittedTest_rf_AK = AK_rf_cv.transform(AK_test)
```

[337]:
```
print('accuracy: '+ str(evaluator.evaluate(fittedTest_rf_AK, {evaluator.
 ↪metricName: "accuracy"})))
print('f1: '+ str(evaluator.evaluate(fittedTest_rf_AK, {evaluator.metricName:␣
 ↪"f1"})))
```

```
23/03/22 23:49:06 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1323.5 KiB
```

```
accuracy: 0.3411016949152542
```

```
23/03/22 23:49:10 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1323.5 KiB
[Stage 32541:=================================================>      (8 + 1) / 9]
```

```
f1: 0.3133987682190856
```

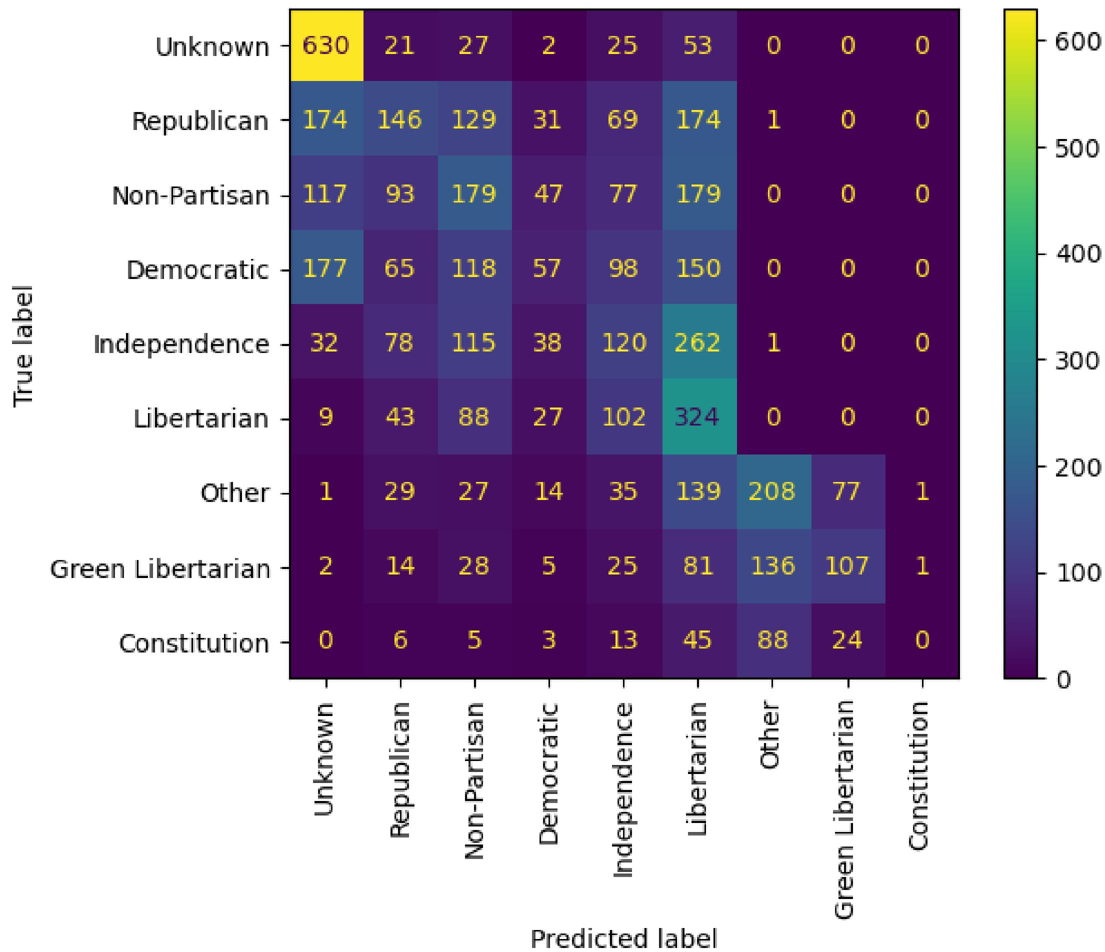
Just like in Logistic Regression, both the accuracy and f1 performance drop significantly, as we try to Classify even more parties. Yet, accuracy being 34% in this scenario is also not bad news.

[338]:
```
y_true_AK = fittedTest_rf_AK.select(['label']).collect()
y_pred_AK = fittedTest_rf_AK.select(['prediction']).collect()
```

```
23/03/22 23:49:17 WARN org.apache.spark.scheduler.DAGScheduler: Broadcasting
large task binary with size 1310.8 KiB
```

[339]:
```
party_names =␣
↪['Unknown','Republican','Non-Partisan','Democratic','Independence','Libertarian','Other',
              'Green Libertarian','Constitution']
cm = confusion_matrix(y_true_AK, y_pred_AK)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=party_names)
disp.plot(xticks_rotation='vertical')
```

[339]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f55893156d0>
```



As we see here, the model gets lost in classification a little, and clearly struggles with classifying Democratic and Constitution parties (Constitution missing is explained clearly in Logistic Regression section).

[340]:
```
print(DC_rf_cv.bestModel.explainParams().split('\n')[9])
print('\n ')
print(DC_rf_cv.bestModel.explainParams().split('\n')[14])
```

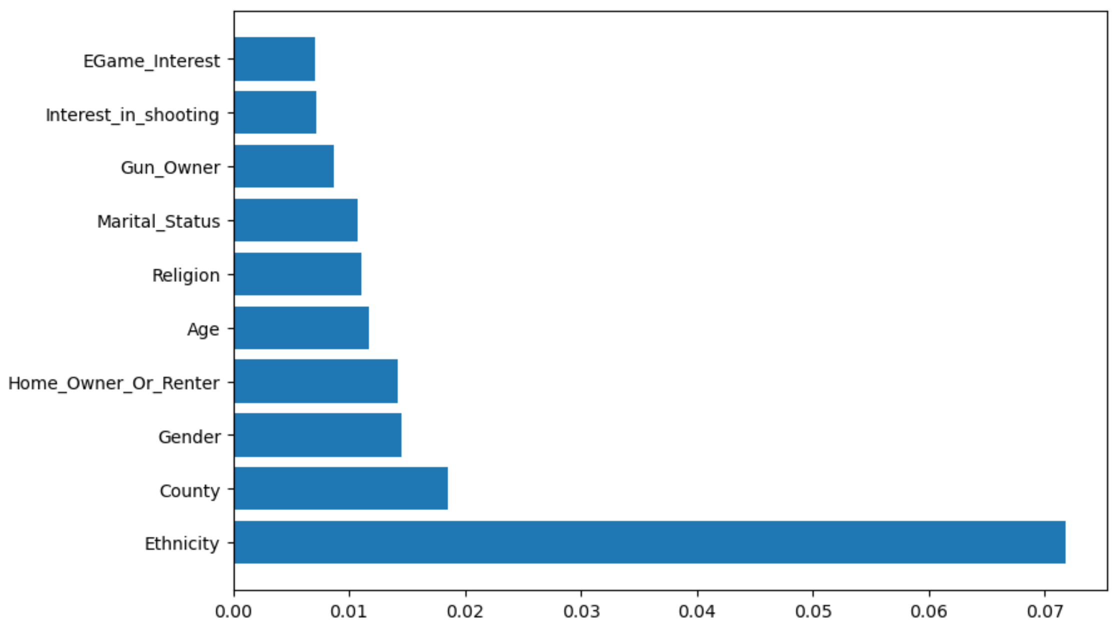
```
maxDepth: Maximum depth of the tree. (>= 0) E.g., depth 0 means 1 leaf node;
depth 1 means 1 internal node + 2 leaf nodes. (default: 5, current: 10)


numTrees: Number of trees to train (>= 1). (default: 20, current: 20)
```

[457]:
```
def get_features_importance(dataset= fittedTest_rf_AK, model=AK_rf_cv):
    """
    Careful! this function is hard-coded inside for feature names.
```

```
    I created earlier `to_encode` and `numerical_cols` lists for Xs names; I'm␣
↪using that here.
    """
    sparse= model.bestModel.featureImportances
    vals= sparse.values
    idx= sparse.indices
    feature_names=dataset.drop('Party','features','label', 'rawPrediction',␣
↪'probability', 'prediction').columns
    importances_df= pd.DataFrame(zip(feature_names, vals), columns=["feature",␣
↪"value"])
    return importances_df
```

[458]:
```
rfc_importance_df= get_features_importance().
 ↪sort_values(by='value',ascending=False)
rfc_importance_df.head(20)
plt.figure(figsize=(9,6))
plt.barh(rfc_importance_df['feature'][:20],
        rfc_importance_df['value'][:20])
```

[458]: <BarContainer object of 10 artists>



In Alaska, Ethinicity being classified as the most important feature, and then followed by County and Gender.

Due to the nature of Random Forest Classifier, unable to go into more details with Coefficients matrix (because Random Forest doesnt support it) and see which specific Ethnicities,Gender, and Religion, play a bigger role voting for one party or the other. But the accuracy of the prediction being similar to the Logistic Regression, I'd suggest going to that section and obtain the needed information.

2.1.7 Naive Bayes

[345]:
```
nb_params = ParamGridBuilder() \
                .addGrid(nb.smoothing, [0.0, 0.2, 0.4, 0.6, 0.8, 1.0]) \
                .build()
nb_cv = CrossValidator(estimator=nb, estimatorParamMaps=nb_params,␣
 ↪evaluator=evaluator, numFolds=3, seed=33)
```

The main tuning parameter for the naive bayes model is smoothing, a shrinkage estimator. Smoothing helps handle the problem of zero probability and avoids overflow.

Washington D.C.

[346]:
```
DC_nb_cv = nb_cv.fit(DC_train)
```

[347]:
```
fittedTest_nb_DC = DC_nb_cv.transform(DC_test)
```

[348]:
```
print('accuracy: '+ str(evaluator.evaluate(fittedTest_nb_DC, {evaluator.
 ↪metricName: "accuracy"})))
print('f1: '+ str(evaluator.evaluate(fittedTest_nb_DC, {evaluator.metricName:␣
 ↪"f1"})))
```

```
accuracy: 0.5301851354977194

[Stage 33041:================================================>       (6 + 1) / 7]

f1: 0.5192723657044781
```

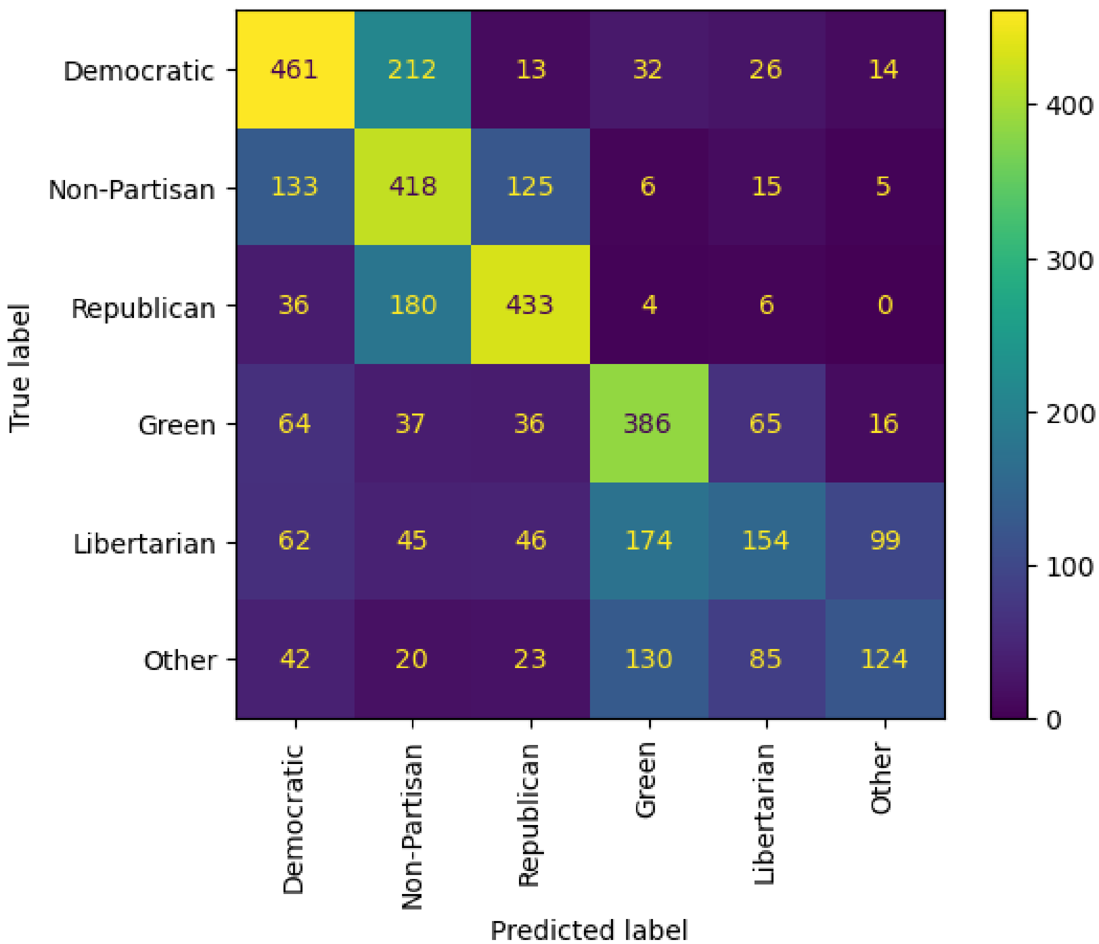
The accuracy for the model for Washington D.C. is roughly 0.53 and f1 is roughly 0.52. Although these seem relatively low considering it only classifies party correctly roughly half the time, we have to consider there are 6 different parties being classified, and the third party ones may have little to no distinction. Thus, a confusion matrix would be helpful to visualize where the classsification is differing for this model.

[349]:
```
y_true_nb = fittedTest_nb_DC.select(['label']).collect()
y_pred_nb = fittedTest_nb_DC.select(['prediction']).collect()
```

[350]:
```
party_names =␣
 ↪['Democratic','Non-Partisan','Republican','Green','Libertarian','Other']
cm = confusion_matrix(y_true_nb, y_pred_nb)
```

```python
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=party_names)
disp.plot(xticks_rotation='vertical')
```

[350]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f558bb47f70>
```



It appears that Democrats are pretty accurately predicted, but will get confused with Non-Partisan the most. Similarly, Non-Partisan also may be labeled as Democrat. Republicans are pretty accurately classified and will accidentally be labeled as Republican. This signals more data is likely needed to distinguish Non-Partisan. Green party voters are nearly always classified correctly. Libertarians and Other are surprisingly labeled as Green Party quite frequently.

[351]:
```python
print(classification_report(y_true_nb, y_pred_nb))
```

```
              precision    recall  f1-score   support

         0.0       0.58      0.61      0.59       758
         1.0       0.46      0.60      0.52       702
```

```
         2.0       0.64      0.66      0.65       659
         3.0       0.53      0.64      0.58       604
         4.0       0.44      0.27      0.33       580
         5.0       0.48      0.29      0.36       424

    accuracy                           0.53      3727
   macro avg       0.52      0.51      0.51      3727
weighted avg       0.53      0.53      0.52      3727
```

[352]:
```
print(DC_nb_cv.bestModel.explainParams().split('\n')[6])
```

```
smoothing: The smoothing parameter, should be >= 0, default is 1.0 (default:
1.0, current: 0.8)
```

This indicates a smoothing value of 0.8 works best for classification in Washington D.C.

[384]:
```
featureImportances = DC_nb_cv.bestModel.theta.toArray().tolist()
featureImportances = featureImportances[0]
```

[380]:
```
fittedTest_nb_DC.select('label', 'prediction').distinct().show()

DCfeaturedCols = pd.DataFrame(fittedTest_nb_DC.schema["features"].
 ↪metadata["ml_attr"]["attrs"]["binary"]+
fittedTest_nb_DC.schema["features"].metadata["ml_attr"]["attrs"]["numeric"]).
 ↪sort_values("idx")
DCfeaturedCols = DCfeaturedCols.set_index('idx')
keys = np.array(DCfeaturedCols).transpose().tolist()
keys = keys[0]
```

```
[Stage 33144:=======================>                              (3 + 1) / 7]

+-----+----------+
|label|prediction|
+-----+----------+
|  0.0|       5.0|
|  0.0|       1.0|
|  0.0|       4.0|
|  0.0|       0.0|
|  0.0|       2.0|
|  0.0|       3.0|
|  1.0|       1.0|
|  1.0|       0.0|
|  1.0|       4.0|
|  1.0|       5.0|
|  1.0|       2.0|
|  1.0|       3.0|
|  2.0|       0.0|
|  2.0|       2.0|
```

```
|  2.0|       3.0|
|  2.0|       4.0|
|  2.0|       1.0|
|  3.0|       5.0|
|  3.0|       2.0|
|  3.0|       1.0|
+-----+----------+
only showing top 20 rows
```

[398]:
```
combined = {keys[i]: featureImportances[i] for i in range(len(keys))}
print(sorted(combined.items(), key=lambda x:x[1]))
```

```
[('Zip_20037', -11.793061638603955), ('Zip_20052', -11.793061638603955),
('Zip_20057', -11.793061638603955), ('Zip_20059', -11.793061638603955),
('Zip_20004', -11.793061638603955), ('Zip_20500', -11.793061638603955),
('Zip_20373', -11.793061638603955), ('Zip_20422', -11.793061638603955),
('Zip_20431', -11.793061638603955), ('Zip_20012', -10.982131422387626),
('Zip_20018', -10.540298670108587), ('Zip_20015', -10.540298670108587),
('Religion_Other', -10.234917020557404), ('Zip_20007', -10.234917020557404),
('Zip_20008', -10.234917020557404), ('Zip_20006', -10.234917020557404),
('Zip_20036', -10.001302169375899), ('Zip_20005', -10.001302169375899),
('Zip_20020', -9.812060169737371), ('Zip_20016', -9.812060169737371),
('Zip_20017', -9.812060169737371), ('Zip_20032', -9.812060169737371),
('Zip_20024', -9.652995475107684), ('Religion_Islamic', -9.515794353594199),
('Religion_Catholic', -9.101818555818125), ('Zip_20019', -8.945249495126586),
('Zip_20010', -8.809908147256824), ('Zip_20011', -8.636061217453841),
('Zip_20003', -8.142403397310215), ('Marital_Status_Married',
-8.079489571899646), ('Zip_20009', -7.911497840660517), ('Religion_Jewish',
-7.495776232385164), ('Ethnicity_Hispanic', -7.398612483931516),
('Ethnicity_German', -7.398612483931516), ('Ethnicity_Unknown',
-6.986993510248973), ('Home_Owner_Or_Renter_Unknown', -6.735224743023404),
('Ethnicity_English/Welsh', -6.477395633721304), ('Religion_Protestant',
-6.303091387833079), ('Ethnicity_Other', -6.177200045320224), ('Zip_20002',
-5.706855254986287), ('Gender_M', -4.898138338437196), ('Gender_F',
-4.806264152281865), ('Ethnicity_Likely Af-Am (Modeled)', -4.568854631173956),
('Zip_20001', -4.455311253770375), ('Religion_Unknown', -4.278398127178782),
('Home_Owner_Or_Renter_Likely Renter', -4.228563860955672), ('Marital_Status_Not
Married', -4.144083555830309), ('EGame_Interest_No', -4.115892823608422),
('Interest_in_shooting_No', -4.115892823608422), ('Gun_Owner_No',
-4.109542862884639), ('Age', -0.15768847888019977)]
```

Alaska

[399]:
```
AK_nb_cv = nb_cv.fit(AK_train)
```

[400]:
```
fittedTest_nb_AK = AK_nb_cv.transform(AK_test)
```

[401]:
```
print('accuracy: '+ str(evaluator.evaluate(fittedTest_nb_AK, {evaluator.
 ↪metricName: "accuracy"})))
print('f1: '+ str(evaluator.evaluate(fittedTest_nb_AK, {evaluator.metricName:␣
 ↪"f1"})))
```

```
accuracy: 0.32492295839753466
```

```
[Stage 33803:====================================>                          (5 + 1) / 8]
```

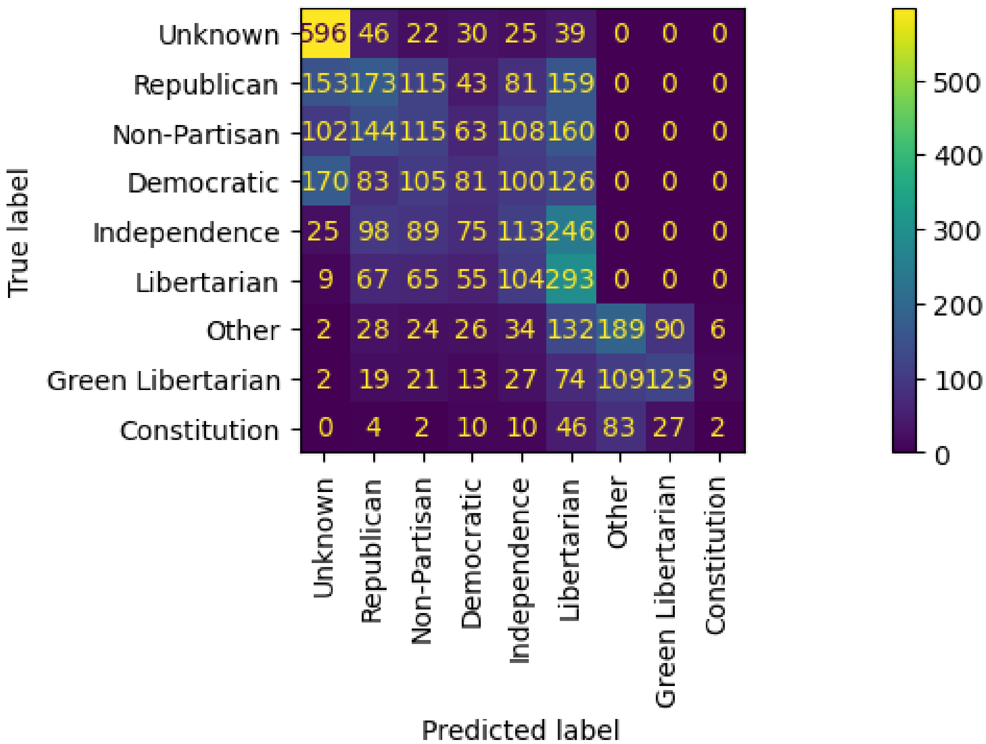
```
f1: 0.30609501366294944
```

The accuracy for the model for Alaska is roughly 0.32 and f1 is roughly 0.31. These seem like low metrics considering it only classifies party correctly roughly a third of the time, we have to consider there are 9 different parties being classified, and the third party ones may have little to no distinction and there are lots of unknown values. Thus, a confusion matrix would be helpful to visualize where the classsification is differing for this model.

[402]:
```
y_true_nb = fittedTest_nb_AK.select(['label']).collect()
y_pred_nb = fittedTest_nb_AK.select(['prediction']).collect()
```

[403]:
```
party_names =␣
 ↪['Unknown','Republican','Non-Partisan','Democratic','Independence','Libertarian','Other',
               'Green Libertarian','Constitution']
cm = confusion_matrix(y_true_nb, y_pred_nb)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=party_names)
disp.plot(xticks_rotation='vertical')
```

[403]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7f5598205790>
```



It appears that Unknown voters are very accurately predicted, but a lot of the the other parties are accidentally predicted as unknown. Thus, data either needs to be balanced further or additional voter information is necessary. To continue, Independent, Other, Republican and Non-Partisan voters are interestingly classified as Libertarians quite frequently. Also, Constitution voters are hardly ever classified correctly.

[404]:
```
print(classification_report(y_true_nb, y_pred_nb))
```

```
              precision    recall  f1-score   support

         0.0       0.56      0.79      0.66       758
         1.0       0.26      0.24      0.25       724
         2.0       0.21      0.17      0.18       692
         3.0       0.20      0.12      0.15       665
         4.0       0.19      0.17      0.18       646
         5.0       0.23      0.49      0.31       593
         6.0       0.50      0.36      0.41       531
         7.0       0.52      0.31      0.39       399
         8.0       0.12      0.01      0.02       184

    accuracy                           0.32      5192
   macro avg       0.31      0.30      0.28      5192
weighted avg       0.32      0.32      0.31      5192
```

[405]:
```
print(AK_nb_cv.bestModel.explainParams().split('\n')[6])
```

```
smoothing: The smoothing parameter, should be >= 0, default is 1.0 (default:
1.0, current: 0.4)
```

Unlike the best naive bayes model for Washington D.C., the optimal smoothing value is 0.4.

[406]:
```
featureImportances = AK_nb_cv.bestModel.theta.toArray().tolist()
featureImportances = featureImportances[0]
```

[407]:
```
fittedTest_nb_AK.select('label', 'prediction').distinct().show()

AKfeaturedCols = pd.DataFrame(fittedTest_nb_AK.schema["features"].
 ↪metadata["ml_attr"]["attrs"]["binary"]+
fittedTest_nb_AK.schema["features"].metadata["ml_attr"]["attrs"]["numeric"]).
 ↪sort_values("idx")
AKfeaturedCols = AKfeaturedCols.set_index('idx')
keys = np.array(AKfeaturedCols).transpose().tolist()
keys = keys[0]
```

```
[Stage 33861:=============>                                          (2 + 1) / 8]

+-----+----------+
|label|prediction|
+-----+----------+
|  0.0|       5.0|
|  0.0|       1.0|
|  0.0|       4.0|
|  0.0|       0.0|
|  0.0|       2.0|
|  0.0|       3.0|
|  1.0|       1.0|
|  1.0|       0.0|
|  1.0|       4.0|
|  1.0|       5.0|
|  1.0|       2.0|
|  1.0|       3.0|
|  2.0|       0.0|
|  2.0|       2.0|
|  2.0|       3.0|
|  2.0|       4.0|
|  2.0|       1.0|
|  2.0|       5.0|
|  3.0|       5.0|
|  3.0|       2.0|
+-----+----------+
only showing top 20 rows
```

[408]:
```python
combined = {keys[i]: featureImportances[i] for i in range(len(keys))}
print(sorted(combined.items(), key=lambda x:x[1]))
```

```
[('County_MATANUSKA SUSITNA', -12.512674602834466), ('County_FAIRBANKS NORTH
STAR', -12.512674602834466), ('County_KENAI PENINSULA', -12.512674602834466),
('County_JUNEAU', -12.512674602834466), ('County_BETHEL', -12.512674602834466),
('County_KETCHIKAN GATEWAY', -12.512674602834466), ('County_VALDEZ CORDOVA',
-12.512674602834466), ('County_KODIAK ISLAND', -12.512674602834466),
('County_SITKA', -12.512674602834466), ('County_SOUTHEAST FAIRBANKS',
-12.512674602834466), ('County_NOME', -12.512674602834466), ('County_KUSILVAK',
-12.512674602834466), ('County_NORTHWEST ARCTIC', -12.512674602834466),
('County_PRINCE OF WALES HYDER', -12.512674602834466), ('County_NORTH SLOPE',
-12.512674602834466), ('County_HAINES', -12.512674602834466), ('County_YUKON
KOYUKUK', -12.512674602834466), ('County_DENALI', -12.512674602834466),
('County_PETERSBURG', -12.512674602834466), ('County_SKAGWAY',
-12.512674602834466), ('County_HOONAH ANGOON', -12.512674602834466),
('County_WRANGELL', -12.512674602834466), ('County_DILLINGHAM',
-12.512674602834466), ('County_LAKE AND PENINSULA', -12.512674602834466),
('County_BRISTOL BAY', -12.512674602834466), ('Religion_Other',
-9.740085880594686), ('Religion_Eastern Orthodox', -7.922618054656423),
('Religion_Jewish', -7.696433446766434), ('Religion_Catholic',
-7.581804277207073), ('Ethnicity_German', -7.563914712456298),
('Ethnicity_Irish', -7.273576595946401), ('Marital_Status_Married',
-7.273576595946401), ('Religion_Protestant', -6.5764585299569625),
('County_ANCHORAGE', -6.126637388784744), ('Ethnicity_Hispanic',
-5.842542196431373), ('Ethnicity_Unknown', -5.778082942861518),
('Ethnicity_English/Welsh', -5.4818171267183455), ('Ethnicity_Other',
-5.475207717330672), ('Home_Owner_Or_Renter_Likely Renter', -5.166019439657927),
('County_ALEUTIANS EAST', -5.118796312726711), ('Gender_F',
-4.9959693020931395), ('County_ALEUTIANS WEST', -4.844814675167503),
('Home_Owner_Or_Renter_Unknown', -4.819420882228198), ('Gender_M',
-4.682248985014136), ('Religion_Unknown', -4.325097207242956),
('Interest_in_shooting_No', -4.296991991806544), ('Gun_Owner_No',
-4.198577267428661), ('Marital_Status_Not Married', -4.190037505880526),
('EGame_Interest_No', -4.146653199219967), ('Age', -0.14824869215114056)]
```

3 Findings & Conclusion

It appears that a majority of the models for Washington D.C. performed roughly above 50% accuracy and the models for Alaska perform roughly above 30% accuracy. This is to be expected considering there are six labels for D.C. and nine labels for Alaska. Furthermore, considering the unbalanced data of Alaska, we retained unknown party values, which generally led to skewed labels towards unknown versus classifying the correct party. Interestingly, the logistic regression model led to a higher accuracy score for D.C. (~54.2%) but the random forest model led to a higher accuracy score for Alaska (~34.1%). To continue, the model with the lowest accuracy for Washington D.C. was the decision tree model and for Alaska it was tied between the decision tree and naive bayes model. To be fair, there was not too large of a margin of difference amongst models' accuracy. Across states and models, county or zip, religion then ethnicity tended to be the most important features in classification while Age, Egame Interest, Marital Status, Gun ownership, and interest in shooting tended to be least important in determining voter party. Overall, there was not much differentiation of party traits between Alaska and Washington D.C.. Further exploration could lead us to analyze other states in the United States to see if these trends are consistent across the United States or to balance the data set again and rerun our models.