Data102 Final Project Elections

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1 Group Members

1. Sarah Shikanov, sarahshikanov@berkeley.edu
2. James Marquez, jamesamarquez@berkeley.edu
3. Michael Chien, mchien512@berkeley.edu
4. Rachel Fei, wfei@berkeley.edu

[1]:
```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import arviz as az
import geopandas as gp
```

1.1 Load in the Data

[2]:
```
dem_df = pd.read_csv('dem_candidates.csv', encoding='latin1')
rep_df = pd.read_csv('rep_candidates.csv',encoding='latin-1')
```

[3]:
```
poll_data = pd.read_csv('presidential_polls.csv')
```

1.1.1 Dataset was taken from https://www.kaggle.com/fivethirtyeight/2016-election-polls

2 1.0 Data Overview

The democrat and republican data were generated by sampling. This was taken from the class dataset. At quick glance from the our pre processing step below we can see that in our first entry we have a governer running from office for Alabama. At quick glance we can see that the Partisan Lean is heavily negative which means its heavily red. This is consistent with what we would expect from before we began doing anything. We are not worried much about bias as this data is simply a representation of endorsements and the primary. Important features that would be useful if there was a way to get the total contribution with the candidate. We tried merging the dataframes with another dataset but it was very non trivial and thus decided to work with what we had. This dataset is public so all participants are aware of this dataset. As to the granularity each row represents a candidate running for office with endorsements and primary election data.

The 2016 Polling dataset was also generated by sampling. This was a dataset from Kaggle and we decided to use this because the election dataset given only covered endorsements and there weren't very many cool problems we could think of analyzing. Again by looking at the data we can get a quick glance at the polling advantages for each candidate and they seem to be consistent.The participants are aware of the collection and use of the data as it's published by pollsters. We can seUnlike the class dataset the polling dataset is worrisome with selection bias due to the unreliability of some pollsters but there is a column for grade which should help us identify good pollsters. The columns are sufficient in this dataset to perform what we want.

2.1 1.1 Preprocessing.

[62]:
```
dem_df['Party'] = "Democrat"
rep_df['Party'] = 'Republican'
```

[63]:
```
df = pd.concat([dem_df, rep_df])
df
```

[63]:
```
                     Candidate State             District Office Type Race Type  \
0     Anthony White (Alabama)    AL  Governor of Alabama    Governor   Regular
1      Christopher Countryman    AL  Governor of Alabama    Governor   Regular
2       Doug "New Blue" Smith    AL  Governor of Alabama    Governor   Regular
3             James C. Fields    AL  Governor of Alabama    Governor   Regular
4               Sue Bell Cobb    AL  Governor of Alabama    Governor   Regular
..                        …   …                  …         …        …
769               Bill Dahlin    WY  Governor of Wyoming    Governor   Regular
770           Harriet Hageman    WY  Governor of Wyoming    Governor   Regular
771              Sam Galeotos    WY  Governor of Wyoming    Governor   Regular
772             Foster Friess    WY  Governor of Wyoming    Governor   Regular
773             Taylor Haynes    WY  Governor of Wyoming    Governor   Regular

    Race Primary Election Date Primary Status Primary Runoff Status  \
0                       6/5/18           Lost                  None
1                       6/5/18           Lost                  None
2                       6/5/18           Lost                  None
3                       6/5/18           Lost                  None
4                       6/5/18           Lost                  None
..                         …              …                     …
769                    8/21/18           Lost                  None
770                    8/21/18           Lost                  None
771                    8/21/18           Lost                  None
772                    8/21/18           Lost                  None
773                    8/21/18           Lost                  None

    General Status  Partisan Lean  …  Great America Endorsed? NRA Endorsed?  \
0             None     -28.879999  …                      NaN           NaN
1             None     -28.879999  …                      NaN           NaN
2             None     -28.879999  …                      NaN           NaN
3             None     -28.879999  …                      NaN           NaN
```

```
4             None     -28.879999  …                      NaN           NaN
..              …             …   …                     …           …
769           None            NaN  …                      NaN           NaN
770           None            NaN  …                      NaN           NaN
771           None            NaN  …                      NaN           NaN
772           None            NaN  …                      NaN           NaN
773           None            NaN  …                      NaN           NaN

    Right to Life Endorsed?  Susan B. Anthony Endorsed?  \
0                       NaN                         NaN
1                       NaN                         NaN
2                       NaN                         NaN
3                       NaN                         NaN
4                       NaN                         NaN
..                      …                         …
769                      No                         NaN
770                     Yes                         NaN
771                     Yes                         NaN
772                     Yes                         NaN
773                     Yes                         NaN

     Club for Growth Endorsed?  Koch Support?  House Freedom Support?  \
0                          NaN            NaN                     NaN
1                          NaN            NaN                     NaN
2                          NaN            NaN                     NaN
3                          NaN            NaN                     NaN
4                          NaN            NaN                     NaN
..                         …            …                     …
769                        NaN            NaN                     NaN
770                        NaN            NaN                     NaN
771                        NaN            NaN                     NaN
772                        NaN            NaN                     NaN
773                        NaN            NaN                     NaN

     Tea Party Endorsed?  Main Street Endorsed?  Chamber Endorsed?
0                    NaN                    NaN                NaN
1                    NaN                    NaN                NaN
2                    NaN                    NaN                NaN
3                    NaN                    NaN                NaN
4                    NaN                    NaN                NaN
..                   …                    …                …
769                  NaN                    NaN                NaN
770                  NaN                    NaN                NaN
771                  NaN                    NaN                NaN
772                  NaN                    NaN                NaN
773                  NaN                    NaN                NaN
```

```
[1563 rows x 46 columns]
```

[6]:
```
# Democrats have weird NaN values for candidates who advanced as well as␣
↪candidateas who lost so we drop these values
# there are 22 of them.
# Repblicans have 0 so we don't have to do anything.
bad_indices = list(dem_df[(dem_df['Won Primary'].isna())].index)
dem_df = dem_df.drop(bad_indices);
```

[7]:
```
# Treat a Nan Value as 0 and the encode no and yes as 0 and 1s.
df.fillna(0, inplace=True)
df.replace('No', 0, inplace=True)
df.replace('Yes', 1, inplace=True)
```

[8]:
```
# Get a list of all democrat and republican endorsements
dem_endorsements = list(df.columns[13:32])
rep_endorsements = list(df.columns[33:46])
endorsements = dem_endorsements + rep_endorsements
```

3 2.0 EDA

3.1 2.1 EDA on 2018 Primary Election Dataset

Lets begin with some EDA on our dataest with republicans and democrats from five thirty eight.

[9]:
```
dem_endorsements
```

[9]:
```
['Veteran?',
 'LGBTQ?',
 'Elected Official?',
 'Self-Funder?',
 'STEM?',
 'Obama Alum?',
 'Party Support?',
 'Emily Endorsed?',
 'Guns Sense Candidate?',
 'Biden Endorsed?',
 'Warren Endorsed? ',
 'Sanders Endorsed?',
 'Our Revolution Endorsed?',
 'Justice Dems Endorsed?',
 'PCCC Endorsed?',
 'Indivisible Endorsed?',
 'WFP Endorsed?',
 'VoteVets Endorsed?',
 'No Labels Support?']
```

We have a prior belief that some endorsements matter more than others. For example we take that Party Support should have a big impact on the number of votes one receives. In addition we think that big names such as Sanders and Biden.

[10]:
```
dem_df.fillna(0, inplace=True)
dem_df.replace('No', 0, inplace=True)
dem_df.replace('Yes', 1, inplace=True)
```

[11]:
```
dem_endorsements_df = dem_df[['Candidate'] + dem_endorsements + ['Won Primary']]
dem_endorsements_df
```

[11]:
```
                    Candidate  Veteran?  LGBTQ?  Elected Official?  \
0     Anthony White (Alabama)         1       0                  0
1      Christopher Countryman         0       1                  0
2       Doug "New Blue" Smith         1       0                  0
3             James C. Fields         1       0                  1
4               Sue Bell Cobb         0       0                  1
..                        ...       ...     ...                ...
806            Talley Sergent         0       0                  0
807           Janice Hagerman         0       0                  0
808                Paul Davis         0       0                  0
809            Richard Ojeda          1       0                  1
810              Shirley Love         0       0                  0

     Self-Funder?  STEM?  Obama Alum?  Party Support?  Emily Endorsed?  \
0               0      0            0               0                0
1               0      0            0               0                0
2               0      0            0               0                0
3               0      0            0               0                0
4               0      0            0               0                0
..            ...    ...          ...             ...              ...
806             0      0            1               0                0
807             0      0            0               0                0
808             0      0            0               0                0
809             0      0            0               0                0
810             0      0            0               0                0

     Guns Sense Candidate?  ...  Warren Endorsed?  Sanders Endorsed?  \
0                        0  ...                 0                  0
1                        0  ...                 0                  0
2                        0  ...                 0                  0
3                        0  ...                 0                  0
4                        0  ...                 0                  0
..                     ...  ...               ...                ...
806                      0  ...                 0                  0
807                      0  ...                 0                  0
808                      0  ...                 0                  0
```

```
809                  0  …              0                  0
810                  0  …              0                  0

     Our Revolution Endorsed?  Justice Dems Endorsed?  PCCC Endorsed?  \
0                           0                       0               0
1                           0                       0               0
2                           0                       0               0
3                           0                       0               0
4                           0                       0               0
..                        …                      …             …
806                         0                       0               0
807                         0                       0               0
808                         0                       0               0
809                         0                       0               0
810                         0                       0               0

     Indivisible Endorsed?  WFP Endorsed?  VoteVets Endorsed?  \
0                        0              0                   0
1                        0              0                   0
2                        0              0                   0
3                        0              0                   0
4                        0              0                   0
..                     …           …                 …
806                      0              0                   0
807                      0              0                   0
808                      0              0                   0
809                      0              1                   1
810                      0              0                   0

     No Labels Support?  Won Primary
0                     0            0
1                     0            0
2                     0            0
3                     0            0
4                     0            0
..                  …          …
806                   0            1
807                   0            0
808                   0            0
809                   0            1
810                   0            0

[789 rows x 21 columns]
```

[12]:

```
dem_copy = dem_df.copy()
dem_copy = dem_df[['Party Support?', 'Biden Endorsed?', 'Sanders Endorsed?'] +␣
 ↪['Primary %']]
```

```
dem_copy
```

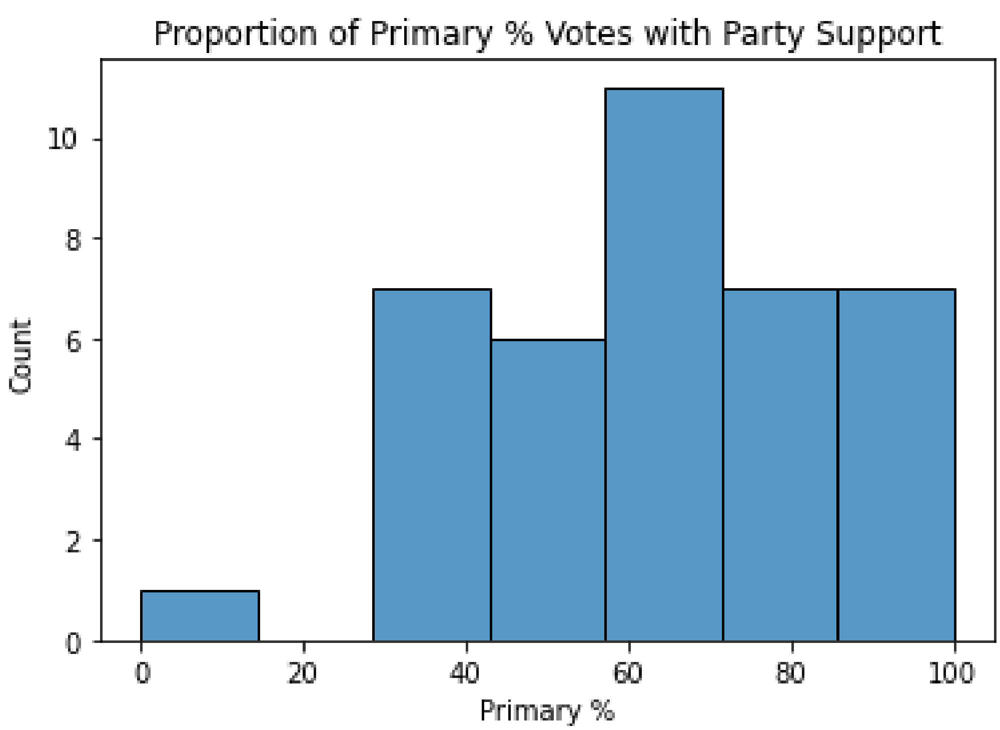
[12]:

```
     Party Support?  Biden Endorsed?  Sanders Endorsed?  Primary %
0                 0                0                  0   3.420000
1                 0                0                  0   1.740000
2                 0                0                  0   3.270000
3                 0                0                  0   8.000000
4                 0                0                  0  28.980000
..              …                …                  …        …
806               0                0                  0  62.570000
807               0                0                  0   7.240000
808               0                0                  0  15.960000
809               0                0                  0  52.160000
810               0                0                  0  24.639999

[789 rows x 4 columns]
```

[13]:

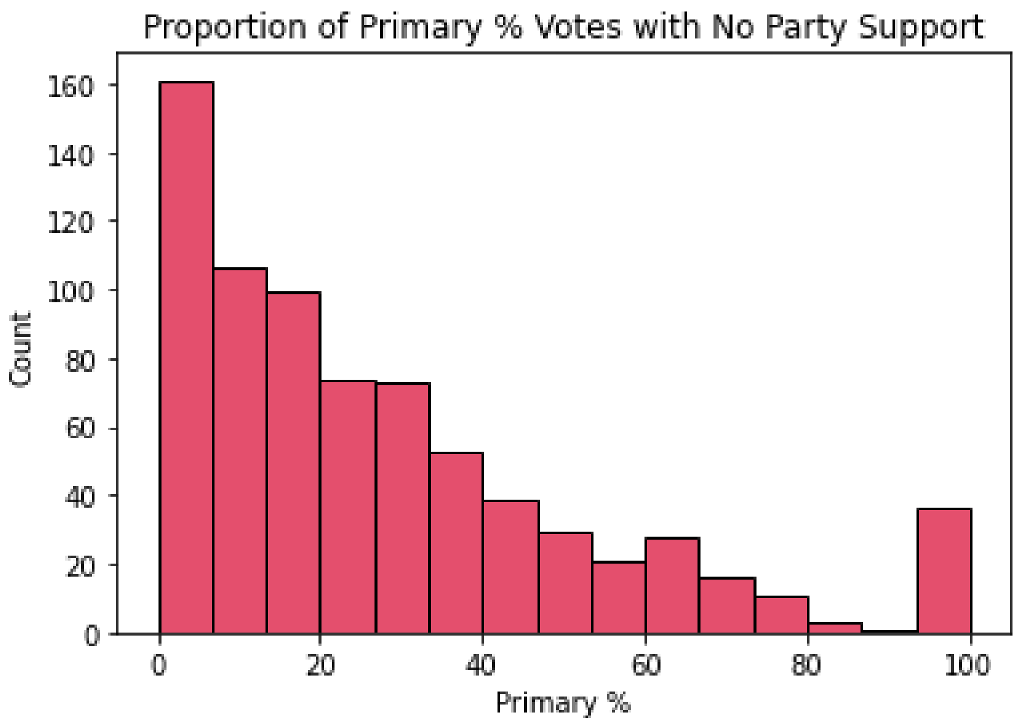
```
party_support = dem_copy[dem_copy['Party Support?'] == 1]
sns.histplot(party_support['Primary %'])
plt.title('Proportion of Primary % Votes with Party Support')
party_support.shape
```

[13]: (39, 4)



[14]:
```python
no_party_support = dem_copy[dem_copy['Party Support?'] == 0]
sns.histplot(no_party_support['Primary %'], color='crimson')
plt.title('Proportion of Primary % Votes with No Party Support')
no_party_support.shape
```

[14]: (750, 4)



From here we can see that party support is quite important. The histogram with no party support is right skewed wit many of the votes not even above 50%. Out of 750 candidates there is a few percentage that is above 50% compared to the first histogram. We should keep this in mind when building our model.

Let's see if we can get a good view of partisan lean based on the state.

[26]:
```python
df_copy = df.copy()
df_copy = df[['Partisan Lean', 'State']]
df_copy = df_copy.groupby(by=['State']).mean()
df_copy.reset_index().head(5)
```

[26]:

	State	Partisan Lean
0	AK	0.000000
1	AL	-36.023125
2	AR	-23.818889
3	AZ	-1.637333

```
4    CA      -0.819133
```

[27]:
```
map_us.head(5)
```

[27]:
```
  STATEFP   STATENS     AFFGEOID GEOID STUSPS                 NAME LSAD  \
0      06  01779778  0400000US06    06     CA           California   00
1      11  01702382  0400000US11    11     DC  District of Columbia   00
2      12  00294478  0400000US12    12     FL              Florida   00
3      13  01705317  0400000US13    13     GA              Georgia   00
4      16  01779783  0400000US16    16     ID                Idaho   00

          ALAND       AWATER     region  \
0  403483823181  20483271881       West
1     158350578     18633500  Northeast
2  138903200855  31407883551  Southeast
3  148963503399   4947080103  Southeast
4  214045425549   2397728105       West

                                            geometry
0  MULTIPOLYGON Z (((-118.59397 33.46720 0.00000,…
1  POLYGON Z ((-77.11976 38.93434 0.00000, -77.04…
2  MULTIPOLYGON Z (((-81.81169 24.56874 0.00000, …
3  POLYGON Z ((-85.60516 34.98468 0.00000, -85.47…
4  POLYGON Z ((-117.24303 44.39097 0.00000, -117…
```

[28]:
```
map_us = gp.read_file('usa-states-census-2014.shp')
map_us.dtypes
```

[28]:
```
STATEFP       object
STATENS       object
AFFGEOID      object
GEOID         object
STUSPS        object
NAME          object
LSAD          object
ALAND          int64
AWATER         int64
region        object
geometry    geometry
dtype: object
```

[31]:
```
map_us.join(df_copy)

bad_states = ['Commonwealth of the Northern Mariana Islands', 'Guam', 'United␣
↪States Virgin Islands',
              'American Samoa', 'Puerto Rico', 'District of Columbia']
```

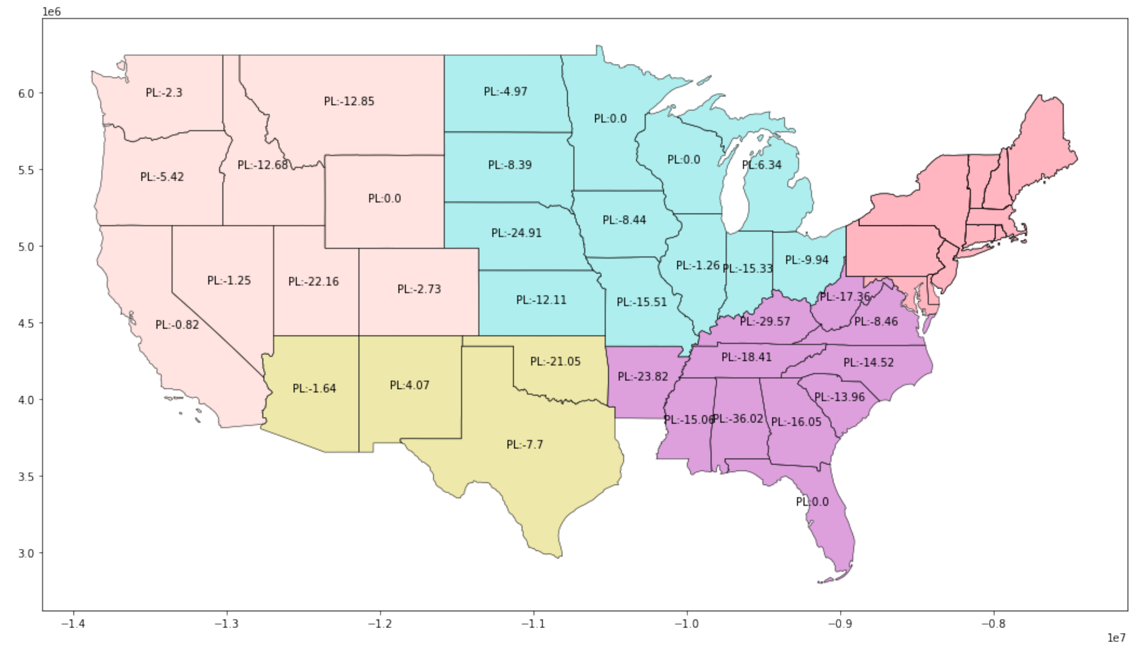
```
map_us_copy = map_us.copy()
map_us_copy = map_us[~map_us.NAME.isin(bad_states)]
map_us_copy = map_us_copy.sort_values(by='NAME')
new_map = pd.merge(map_us_copy, df_copy, left_on='STUSPS', right_on='State')
```

[37]:
```
new_map = new_map.to_crs('EPSG:3395',);
```

[40]:
```
new_map = new_map.round({'Partisan Lean': 2})
```

[41]:
```
# Code adpated from https://jcutrer.com/python/learn-geopandas-plotting-usmaps
ax = new_map.boundary.plot(figsize=(18, 12), color='Black', linewidth=.5)
west = new_map[new_map['region'] == 'West']
southwest = new_map[new_map['region'] == 'Southwest']
southeast = new_map[new_map['region'] == 'Southeast']
midwest = new_map[new_map['region'] == 'Midwest']
northeast = new_map[new_map['region'] == 'Northeast']

west.apply(
    lambda x: ax.annotate(
        text="PL:" + str(x['Partisan Lean']),
        xy= (x.geometry.centroid.coords[0]),
        ha='center',
        color='#000000',
        fontsize=10),axis=1);

southwest.apply(
    lambda x: ax.annotate(
        text="PL:" + str(x['Partisan Lean']),
        xy= (x.geometry.centroid.coords[0]),
        ha='center',
        color='#000000',
        fontsize=10),axis=1);

southeast.apply(
    lambda x: ax.annotate(
        text="PL:" + str(x['Partisan Lean']),
        xy= (x.geometry.centroid.coords[0]),
        ha='center',
        color='#000000',
        fontsize=10),axis=1);

midwest.apply(
    lambda x: ax.annotate(
        text="PL:" + str(x['Partisan Lean']),
        xy= (x.geometry.centroid.coords[0]),
        ha='center',
        color='#000000',
```

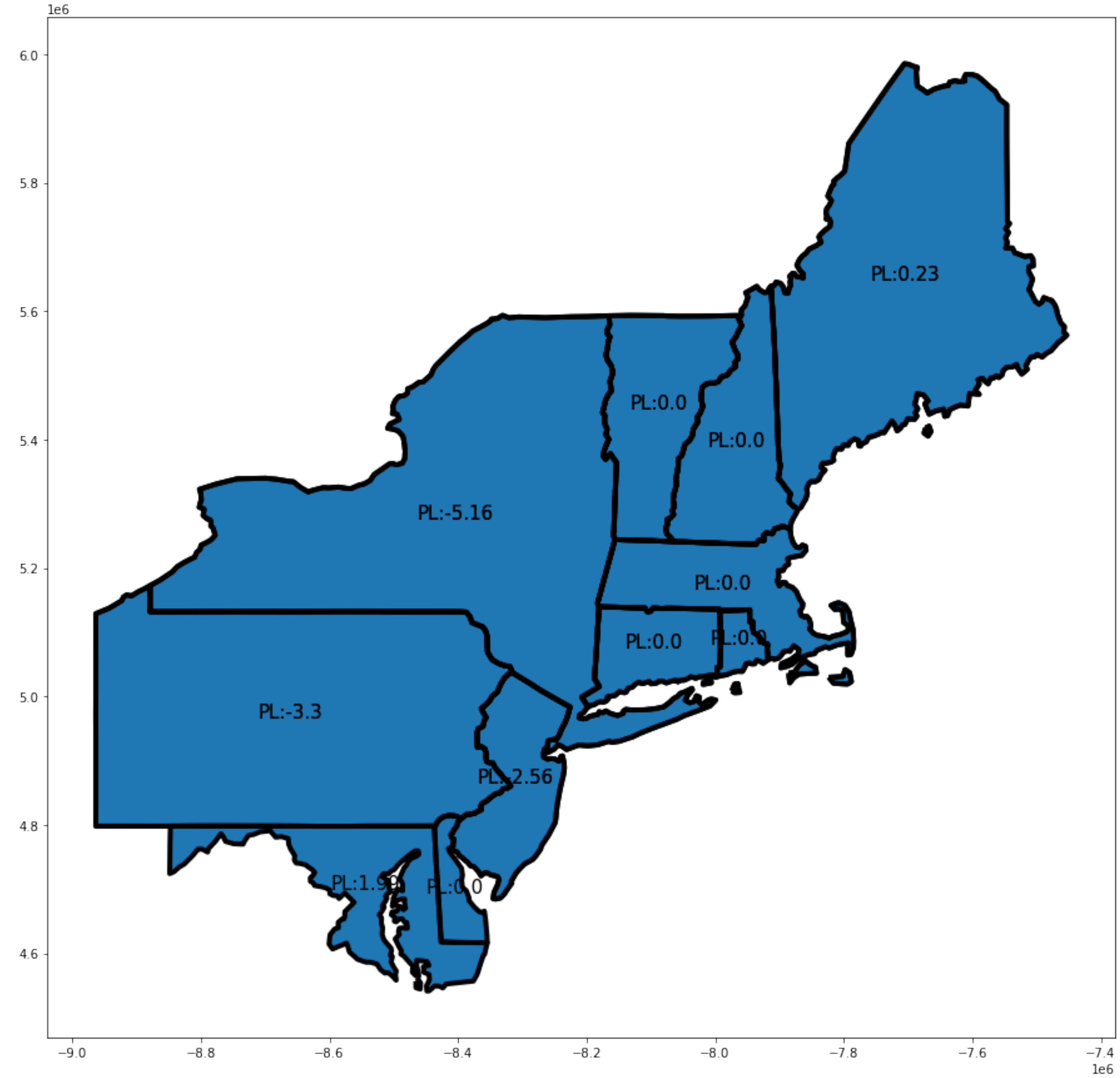
```
        fontsize=10),axis=1);

west.plot(ax=ax,  color="MistyRose")
southwest.plot(ax=ax, color="PaleGoldenRod")
southeast.plot(ax=ax, color="Plum")
midwest.plot(ax=ax, color="PaleTurquoise")
final_map = northeast.plot(ax=ax, color="LightPink")
```



This map is a useful visualization of the partisan leans betwen states. We see that the South is heavily republican while the West is less repbulican and leaning torwards more Democrat. This is quite as expected but can be useful when performing Bayesian Inference.

[43]:
```
fig = plt.figure(1, figsize=(25,15))
ax = fig.add_subplot()
northeast = new_map[new_map['region'] == 'Northeast']
northeast.apply(
    lambda x: ax.annotate(
        text="PL:" + str(x['Partisan Lean']),
        xy= (x.geometry.centroid.coords[0]),
        ha='center',
        color='#000000', # blue
        fontsize=15),axis=1);
northeast.boundary.plot(ax=ax, color ='Black', linewidth=4)
northeast.plot(figsize=(10, 10), ax = ax)
```

[43]: <AxesSubplot:>



As expected with our prior beliefs the northeast seems to have a partisan lean more torwards Democrats!

4 3.0 Nonparameteric Methods/GLMs.

Can we predict if a candidate won the primary based on the number of endorsements/type of endorsement

1. GLM : Logistic Regression because we have a binary decision.
2. Nonparametric Methods: DecisionTree/RandomForest because it again works well with binary decisions and our data should be easily seperable.

4.1 3.1 Nonparametric Methods.

4.1.1 3.1.1 Train Test Split

We will conduct a train test split with 70% of the data being in our training set.

[51]:
```
# Train test split random seed 102
from sklearn.model_selection import train_test_split

train, test = train_test_split(df, train_size = 0.7, test_size = 0.3,␣
↪random_state=10)
```

4.1.2 3.1.2 Feature Engineering

1. We wil create a column of unique endorsements based on the number of endorsements from republicans and democrats.
2. Next we will calculate the proportion of endorsements based on party.

[52]:
```
# Sum over all rows and find the number of unique endorsements.
train.loc[:,'Unique Endorsements'] = train[endorsements].sum(axis = 1)
test.loc[:, 'Unique Endorsements'] = test[endorsements].sum(axis = 1)
```

```
/opt/conda/lib/python3.9/site-packages/pandas/core/indexing.py:1667:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self.obj[key] = value
```

[53]:
```
train.sample(n= 5)
```

[53]:
```
                Candidate State                                District  \
152  Paulette E. Jordan    ID                       Governor of Idaho
726      Pedro Valencia    TX          U.S. House Texas District 29
459           Omar Vaid    NY       U.S. House New York District 11
286      Janet T. Mills    ME                       Governor of Maine
362  David Wilson Brown    NC  U.S. House North Carolina District 10

        Office Type Race Type Race Primary Election Date Primary Status  \
152        Governor   Regular                    5/15/18       Advanced
726  Representative   Regular                     3/6/18           Lost
459  Representative   Regular                    6/26/18           Lost
286        Governor   Regular                    6/12/18       Advanced
362  Representative   Regular                     5/8/18       Advanced

    Primary Runoff Status General Status  Partisan Lean  …  NRA Endorsed?  \
152                  None  On the Ballot     -34.330002  …              0
```

```
726                   None           None      39.970001  …              0
459                   None           None      -8.810000  …              0
286                   None  On the Ballot       3.510000  …              0
362                   None  On the Ballot     -25.510000  …              0

     Right to Life Endorsed? Susan B. Anthony Endorsed?  \
152                        0                          0
726                        0                          0
459                        0                          0
286                        0                          0
362                        0                          0

     Club for Growth Endorsed?  Koch Support?  House Freedom Support?  \
152                          0              0                       0
726                          0              0                       0
459                          0              0                       0
286                          0              0                       0
362                          0              0                       0

     Tea Party Endorsed?  Main Street Endorsed?  Chamber Endorsed?  \
152                    0                      0                  0
726                    0                      0                  0
459                    0                      0                  0
286                    0                      0                  0
362                    0                      0                  0

     Unique Endorsements
152                    3
726                    0
459                    0
286                    2
362                    1

[5 rows x 47 columns]
```

[54]:
```
def calculate_proportion(row):
    if (row['Party'] == 'Democrat'):
        row['Proportion'] = row['Unique Endorsements']/len(dem_endorsements)
    else:
        row['Proportion'] = row['Unique Endorsements']/len(rep_endorsements)
    return row
```

[55]:
```
train = train.apply(lambda row:  calculate_proportion(row), axis = 1)
test = test.apply(lambda row: calculate_proportion(row), axis = 1)
```

[56]:
```
X = train[['Partisan Lean', 'Unique Endorsements', 'Proportion', 'Party Support?
 ↪']]
```

```
y = train['Won Primary']
```

4.1.3 3.1.3 Nonparametric Methods Results.

[182]:
```
from sklearn.linear_model import LogisticRegression as LR

model = LR()
model.fit(X, y)
y_pred = model.predict(X)
y_pred_test = model.predict(test[['Partisan Lean', 'Unique Endorsements',␣
↪'Proportion', 'Party Support?']])

train['pred'] = y_pred
test['pred'] = y_pred_test


from sklearn.metrics import accuracy_score

train_accuracy = accuracy_score(train['pred'], train['Won Primary'])
test_accuracy = accuracy_score(test['pred'], test['Won Primary'])
train_accuracy, test_accuracy
```

[182]:
```
(0.7376014427412083, 0.7016806722689075)
```

We don't have the best accuracy using logistic regression lets see if we can do better with random forest and perhaps our data is not very linearly seperable.

[183]:
```
# These are the columns we will use in our model.
X_col = ['Partisan Lean', 'Unique Endorsements', 'Proportion', 'Party Support?']
y_col = 'Won Primary'
```

[184]:
```
# Predict and add these predictions to our dataframe
from sklearn.ensemble import RandomForestClassifier


tree_model = RandomForestClassifier()
X = train[X_col]
y = train[y_col]
tree_model.fit(X,y)
y_pred = tree_model.predict(X)
y_pred_test = tree_model.predict(test[X_col])

train['tree_pred'] = y_pred
test['tree_pred'] = y_pred_test

from sklearn.metrics import accuracy_score
```

```
train_accuracy = accuracy_score(train['tree_pred'], train['Won Primary'])
test_accuracy = accuracy_score(test['tree_pred'], test['Won Primary'])
train_accuracy, test_accuracy
```

[184]: (0.8151487826871056, 0.6932773109243697)

We will look at our mean squared error.

4.1.4 3.1.4 Interpretation of results

For our first model logistic regression seemed to have trouble linearly seperating the data thus resulting in around 70% accuracy. It

It seems that our training accuracy is not the most acurate at 81% training accuracy. Our test accuracy is even lower and this is most likely due to the fact that we are overfitting our data therefore compromising something in our model. To fix this, better feature selection/feature engineering can help overfitting and will be something to look at to fix for our final project.

4.2 3.2 GLM Model

Next we will look at using a GLM logistic regresion model. We will approach this using a frequentist appraoch then look at it from a bayesian approach.

[225]:
```
from scipy.stats import poisson, norm, gamma
import statsmodels.api as sm

try:
    from pymc3 import *
    import pymc3 as pm
except:
    ! pip install pymc3
    from pymc3 import *
    import pymc3 as pm
```

[57]:
```
# Some glm preprocessing
glm_df = train.copy()
glm_df['Unique Endorsements'] = glm_df[endorsements].sum(axis = 1)
```

4.3 3.2.1 Methods

Again we are trying to predict the same thing as above in our nonparameric methods. We will be using a binomial glm because we have count data and our link function should work for our binary data. We will then evaluate the model by first using a frequentist model and analyzing the deviance and Pearson chi-squared before than analyzing the posterior distribution.

4.4 3.2.2 Results

[18]:
```
# Frequentist GLM
glm_binom = sm.GLM(glm_df['Won Primary'], exog=sm.add_constant(glm_df[X_col]),
                   family=sm.families.Binomial())
glm_res = glm_binom.fit()
print(glm_res.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:            Won Primary   No. Observations:                 1109
Model:                            GLM   Df Residuals:                     1105
Model Family:                Binomial   Df Model:                            3
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -637.71
Date:                Thu, 09 Dec 2021   Deviance:                       1275.4
Time:                        15:02:35   Pearson chi2:                 1.11e+03
No. Iterations:                     4
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
const                  -1.3622      0.096    -14.119      0.000      -1.551
-1.173
Partisan Lean          -0.0150      0.004     -3.542      0.000      -0.023
-0.007
Unique Endorsements    -0.5497      0.265     -2.074      0.038      -1.069
-0.030
Proportion             16.4536      4.596      3.580      0.000       7.445
25.462
================================================================================
=======

/opt/conda/lib/python3.9/site-packages/statsmodels/tsa/tsatools.py:142:
FutureWarning: In a future version of pandas all arguments of concat except for
the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

[19]:
```
glm_df = glm_df.rename(columns={'Won Primary' : 'Won_Primary', 'Unique␣
↪Endorsements' : 'Unique_Endorsements',
                                'Partisan Lean': 'Partisan_Lean'})
```

[20]:
```
# Bayesian GLM
with pm.Model() as bayes_model:
```

```
    glm.GLM.from_formula("Won_Primary ~ + Unique_Endorsements + Partisan_Lean +␣
↪Proportion", glm_df,
                         family = glm.families.Binomial())
    trace_binomial = pm.sample(1000, cores = 1, target_accept = 0.95,␣
↪init='adapt_diag')
```

```
/tmp/ipykernel_24/536276188.py:5: FutureWarning: In v4.0, pm.sample will return
an `arviz.InferenceData` object instead of a `MultiTrace` by default. You can
pass return_inferencedata=True or return_inferencedata=False to be safe and
silence this warning.
  trace_binomial = pm.sample(1000, cores = 1, target_accept = 0.95,
init='adapt_diag')
Auto-assigning NUTS sampler…
Initializing NUTS using adapt_diag…
Sequential sampling (2 chains in 1 job)
NUTS: [Proportion, Partisan_Lean, Unique_Endorsements, Intercept]
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

```
Sampling 2 chains for 1_000 tune and 1_000 draw iterations (2_000 + 2_000 draws
total) took 89 seconds.
```

[21]:
```
pm.summary(trace_binomial)
```

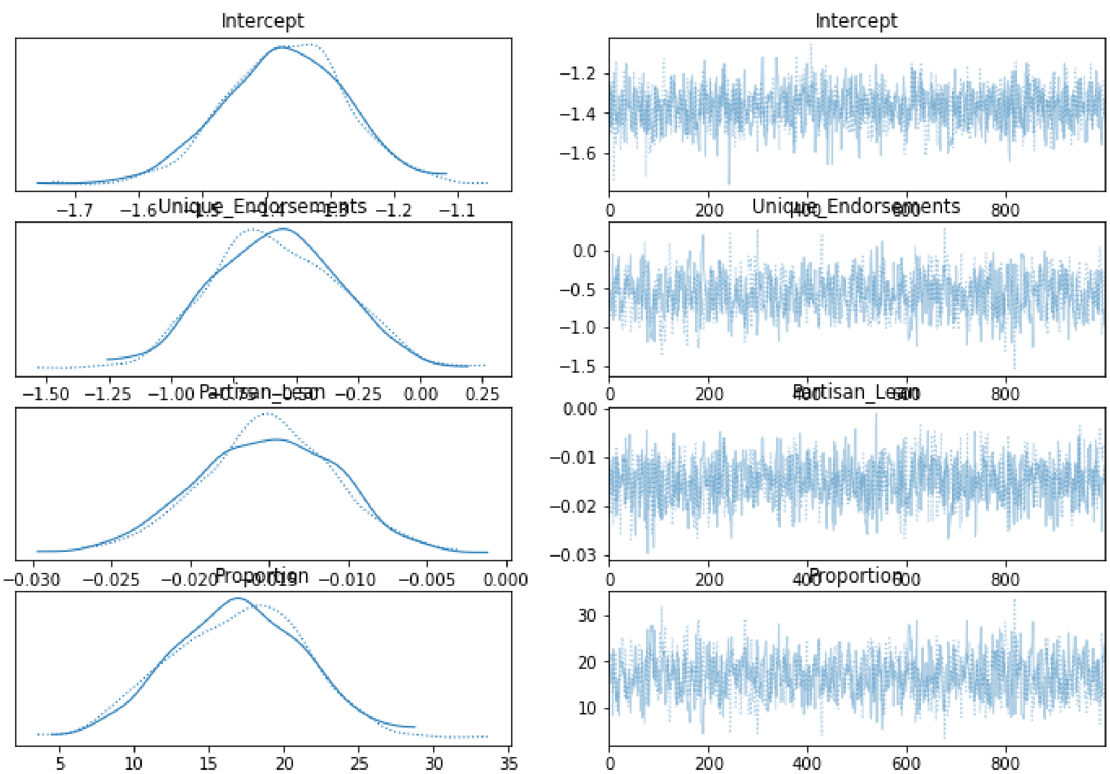
```
Got error No model on context stack. trying to find log_likelihood in
translation.
/opt/conda/lib/python3.9/site-packages/arviz/data/io_pymc3_3x.py:98:
FutureWarning: Using `from_pymc3` without the model will be deprecated in a
future release. Not using the model will return less accurate and less useful
results. Make sure you use the model argument or call from_pymc3 within a model
context.
  warnings.warn(
```

[21]:
```
                       mean     sd  hdi_3%  hdi_97%  mcse_mean  mcse_sd  \
Intercept            -1.371  0.095  -1.562   -1.207      0.003    0.002
Unique_Endorsements  -0.576  0.256  -1.002   -0.073      0.009    0.006
Partisan_Lean        -0.015  0.004  -0.023   -0.007      0.000    0.000
Proportion           16.953  4.430   8.326   24.704      0.158    0.113

                     ess_bulk  ess_tail  r_hat
Intercept              1027.0    1008.0    1.0
Unique_Endorsements     800.0     831.0    1.0
Partisan_Lean           969.0     983.0    1.0
Proportion              780.0     775.0    1.0
```

[22]:
```
az.plot_trace(trace_binomial)
```

```
Got error No model on context stack. trying to find log_likelihood in
translation.
/opt/conda/lib/python3.9/site-packages/arviz/data/io_pymc3_3x.py:98:
FutureWarning: Using `from_pymc3` without the model will be deprecated in a
future release. Not using the model will return less accurate and less useful
results. Make sure you use the model argument or call from_pymc3 within a model
context.
  warnings.warn(
Got error No model on context stack. trying to find log_likelihood in
translation.
```

[22]:
```
array([[<AxesSubplot:title={'center':'Intercept'}>,
        <AxesSubplot:title={'center':'Intercept'}>],
       [<AxesSubplot:title={'center':'Unique_Endorsements'}>,
        <AxesSubplot:title={'center':'Unique_Endorsements'}>],
       [<AxesSubplot:title={'center':'Partisan_Lean'}>,
        <AxesSubplot:title={'center':'Partisan_Lean'}>],
       [<AxesSubplot:title={'center':'Proportion'}>,
        <AxesSubplot:title={'center':'Proportion'}>]], dtype=object)
```

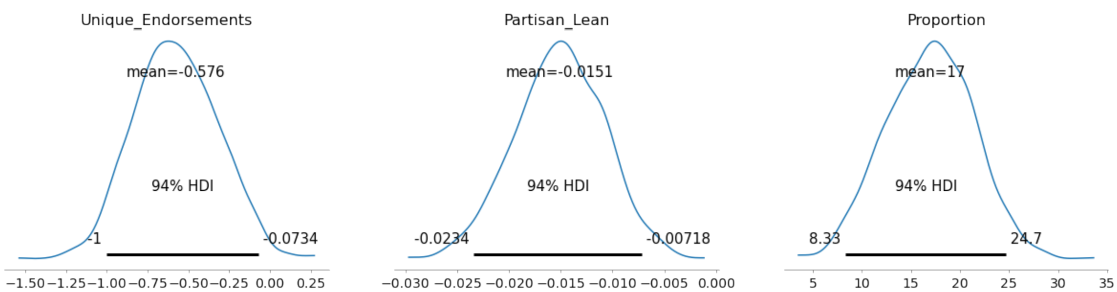


We can also plot the posterior distributions and see their credible intervals.

[23]:
```
# Plot Posterior
az.plot_posterior(trace_binomial, ['Unique_Endorsements', 'Partisan_Lean',␣
↪'Proportion'], round_to=3)
```

```
Got error No model on context stack. trying to find log_likelihood in
translation.
/opt/conda/lib/python3.9/site-packages/arviz/data/io_pymc3_3x.py:98:
FutureWarning: Using `from_pymc3` without the model will be deprecated in a
future release. Not using the model will return less accurate and less useful
results. Make sure you use the model argument or call from_pymc3 within a model
context.
  warnings.warn(
```

[23]:
```
array([<AxesSubplot:title={'center':'Unique_Endorsements'}>,
       <AxesSubplot:title={'center':'Partisan_Lean'}>,
       <AxesSubplot:title={'center':'Proportion'}>], dtype=object)
```

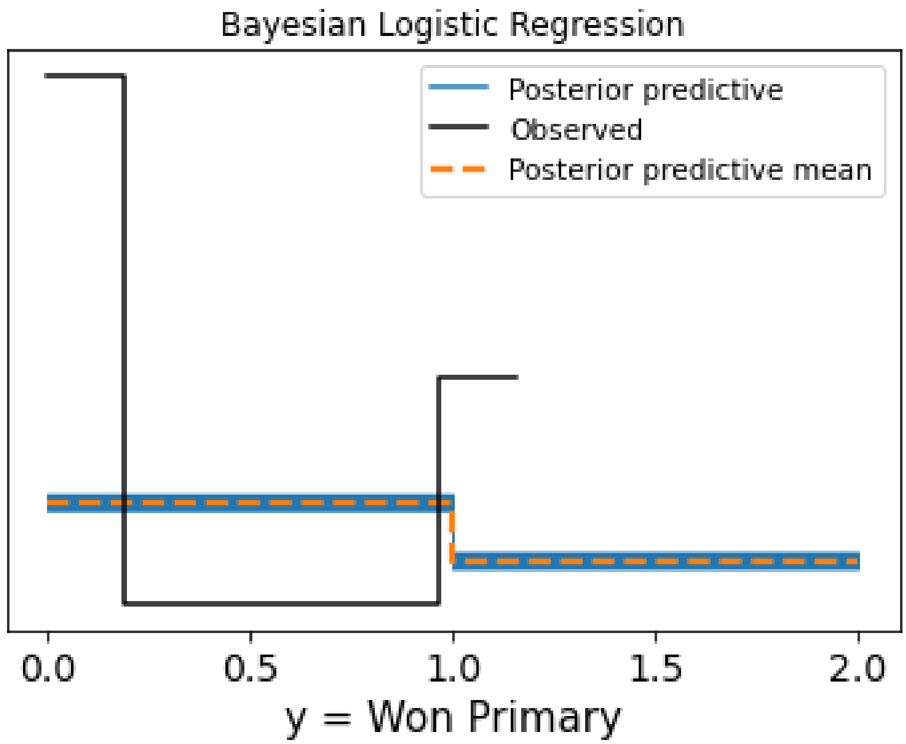


[61]:
```
glm_df['Unique Endorsements'].mean(), glm_df['Partisan Lean'].mean(),␣
↪glm_df['Proportion'].mean()
```

[61]:
```
(0.8917944093778178, -7.363444505509468, 0.05204017187311762)
```

[24]:
```
# Bayesian Posterior Predictive Check
# THERE ARE SOME ISSUES HERE IDK WHY
with bayes_model:
    binomial_ppc = pm.sample_posterior_predictive(trace_binomial)
    ppc_binomial = az.from_pymc3(trace_binomial,␣
↪posterior_predictive=binomial_ppc)

az.plot_ppc(ppc_binomial)
plt.xlabel('y = Won Primary')
plt.title('Bayesian Logistic Regression')
plt.show()
```

```
<IPython.core.display.HTML object>
```



4.4.1 3.2.3 Results for GLM and Comparison to Random Forest

For our frequentist model we see we have a very negative log likelihood which may seem that this is not a good fit for our model. However if we look at the number of observations minus the number of parameters $n-p = 1109-5 = 1104$. Our deviance and chi-square χ^2 is 1275 and 1100 respectively because these are not too off our frequentist model does not seem to be a very good fit.

Comparing to our nonparametric method of random forest we found we had a not terrible training accuracy but not very good test accuracy. We conclucded this must be because of overfitting. However our GLM shows that indeed our model has some problems with our frequentist as well as our bayesian model using posterior predictive checks.

[38]:
```
poll_data = pd.read_csv('presidential_polls.csv')
```

[64]:
```
poll_data.head(2)
```

[64]:
```
    startdate     enddate state                    pollster grade   poll_wt  \
0 2016-10-25 2016-10-31  U.S.    Google Consumer Surveys     B  6.139129
1 2016-10-27 2016-10-30  U.S.   ABC News/Washington Post    A+  4.197292

   samplesize population  adjpoll_clinton  adjpoll_trump
0     24316.0         lv         42.64140       40.86509
1      1128.0         lv         43.29659       44.72984
```

[40]:
```python
poll_data.columns
```

[40]:
```
Index(['cycle', 'branch', 'type', 'matchup', 'forecastdate', 'state',
       'startdate', 'enddate', 'pollster', 'grade', 'samplesize', 'population',
       'poll_wt', 'rawpoll_clinton', 'rawpoll_trump', 'rawpoll_johnson',
       'rawpoll_mcmullin', 'adjpoll_clinton', 'adjpoll_trump',
       'adjpoll_johnson', 'adjpoll_mcmullin', 'multiversions', 'url',
       'poll_id', 'question_id', 'createddate', 'timestamp'],
      dtype='object')
```

[ ]:
```python

```

4.5 4.0 EDA on Polling Data from Kaggle.

We will begin with some EDA to visualzie if we can identify key features or plot data to help form good priors.

4.5.1 Dataset was taken from https://www.kaggle.com/fivethirtyeight/2016-election-polls

[68]:
```python
poll_data = pd.read_csv('presidential_polls.csv')
```

[69]:
```python
poll_data.head(2)
```

[69]:
```
   cycle     branch        type                         matchup forecastdate  \
0   2016  President  polls-plus  Clinton vs. Trump vs. Johnson      11/1/16
1   2016  President  polls-plus  Clinton vs. Trump vs. Johnson      11/1/16

  state   startdate     enddate                   pollster grade  …  \
0  U.S.  10/25/2016  10/31/2016    Google Consumer Surveys     B  …
1  U.S.  10/27/2016  10/30/2016  ABC News/Washington Post    A+  …

   adjpoll_clinton adjpoll_trump  adjpoll_johnson  adjpoll_mcmullin  \
0         42.64140      40.86509         5.675099               NaN
1         43.29659      44.72984         3.401513               NaN

   multiversions                                                url  poll_id  \
0            NaN  https://datastudio.google.com/u/0/#/org//repor…    47940
1            NaN  http://www.langerresearch.com/wp-content/uploa…    47881

   question_id  createddate             timestamp
0        74999      11/1/16  15:09:38  1 Nov 2016
1        74936      11/1/16  15:09:38  1 Nov 2016

[2 rows x 27 columns]
```

[70]:
```python
poll_data.columns
```

[70]:
```
Index(['cycle', 'branch', 'type', 'matchup', 'forecastdate', 'state',
       'startdate', 'enddate', 'pollster', 'grade', 'samplesize', 'population',
       'poll_wt', 'rawpoll_clinton', 'rawpoll_trump', 'rawpoll_johnson',
       'rawpoll_mcmullin', 'adjpoll_clinton', 'adjpoll_trump',
       'adjpoll_johnson', 'adjpoll_mcmullin', 'multiversions', 'url',
       'poll_id', 'question_id', 'createddate', 'timestamp'],
      dtype='object')
```

[71]:
```
poll_data = poll_data[["startdate", "enddate", "state", "pollster", "grade",␣
 ↪'poll_wt',
  "samplesize", "population", "adjpoll_clinton", "adjpoll_trump"]]


poll_data['startdate'] = pd.to_datetime(poll_data["startdate"])
poll_data["enddate"] = pd.to_datetime(poll_data["enddate"])
poll_data.sort_values(by=['startdate', 'enddate'])
```

[71]:
```
      startdate    enddate           state  \
3071 2015-11-06 2015-11-16   New Hampshire
6517 2015-11-06 2015-11-16   New Hampshire
9895 2015-11-06 2015-11-16   New Hampshire
3077 2015-11-07 2015-11-08  South Carolina
6520 2015-11-07 2015-11-08  South Carolina
…           …          …             …
6864 2016-10-30 2016-10-30        Virginia
6872 2016-10-30 2016-10-30         Florida
6881 2016-10-30 2016-10-30        Colorado
6905 2016-10-30 2016-10-30          Nevada
6987 2016-10-30 2016-10-30        Michigan

                                pollster grade       poll_wt  samplesize  \
3071                     Morning Consult   NaN  6.120000e-06       530.0
6517                     Morning Consult   NaN  7.660000e-07       530.0
9895                     Morning Consult   NaN  6.120000e-06       530.0
3077               Public Policy Polling    B+  5.460000e-06      1290.0
6520               Public Policy Polling    B+  6.710000e-07      1290.0
…                                    …   …           …          …
6864                          Remington   NaN  2.282895e+00      1106.0
6872                          Remington   NaN  2.171098e+00       989.0
6881                          Remington   NaN  2.132726e+00       952.0
6905                          Remington   NaN  1.940524e+00       787.0
6987  Mitchell Research & Communications     D  1.417711e+00       953.0

     population  adjpoll_clinton  adjpoll_trump
3071         rv         45.40125       38.46687
6517         rv         45.20979       38.59373
9895         rv         45.39273       38.40193
```

```
3077          v       40.63694      45.19826
6520          v       40.48820      45.19637
…          …           …             …
6864         lv       46.66191      41.12267
6872         lv       43.66191      46.12267
6881         lv       44.66191      42.12267
6905         lv       43.66191      46.12267
6987         lv       45.61794      40.12326

[10236 rows x 10 columns]
```

Next we will identify battleground states based on the difference between the adjusted poll values between Trump and Clinton. If the difference between clinton and the trump poll fall below a value ϵ we will define this as a battleground state.

[72]:
```
df = poll_data.copy()
```

[73]:
```
57.9 + 33
```

[73]:
```
90.9
```

[74]:
```
df_group = df.groupby(by=['state']).mean().reset_index()
df_group.head(5)
```

[74]:

	state	poll_wt	samplesize	adjpoll_clinton	adjpoll_trump
0	Alabama	0.106648	608.968750	32.570923	57.944145
1	Alaska	0.263570	319.310345	35.678765	43.713035
2	Arizona	0.305452	760.866667	41.697958	43.768535
3	Arkansas	0.143535	335.882353	37.011808	50.654389
4	California	0.224925	1275.036364	54.934097	32.294801

[75]:
```
def battleground(row, eps=2):
    if abs(row['adjpoll_clinton'] - row['adjpoll_trump']) < eps:
        row['battleground'] = 1
    else:
        row['battleground'] = 0
    return row
```

[76]:
```
df_group = df_group.apply(lambda row: battleground(row), axis = 1)
```

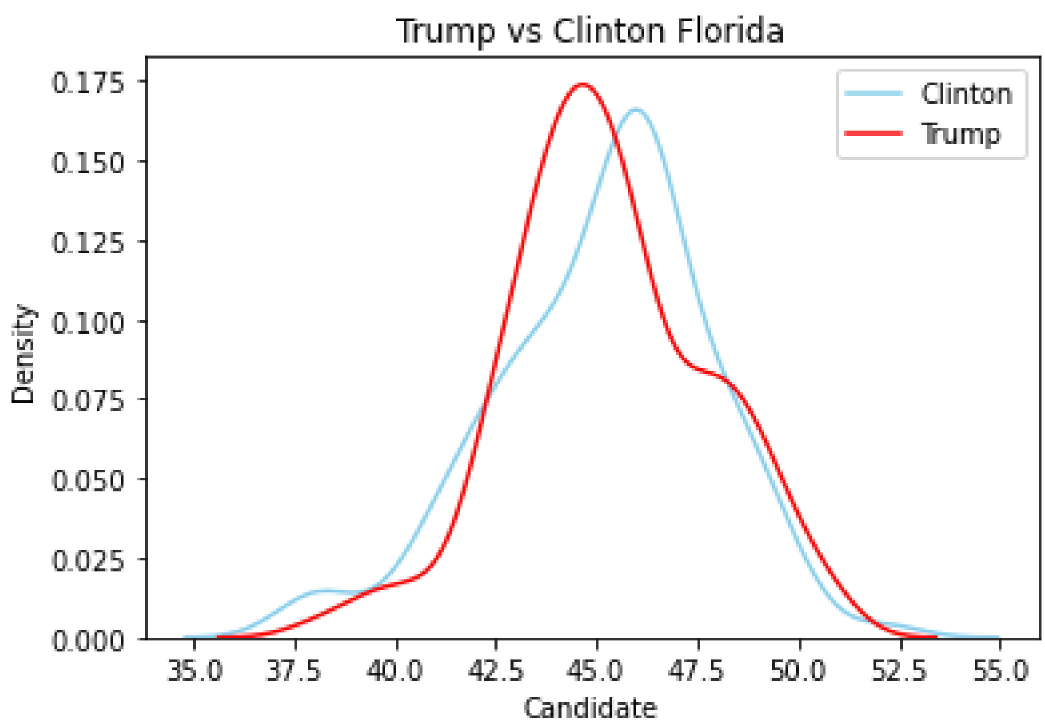
[77]:
```
battleground_states = df_group[df_group['battleground'] == 1]['state']

df[df['state'].isin(battleground_states.tolist())]
battleground_states
```

[77]:
```
9             Florida
15               Iowa
```

```
33             Nevada
38     North Carolina
40               Ohio
Name: state, dtype: object
```

[78]:
```
# Look at florida
fig, ax = plt.subplots()
sns.kdeplot(df[df['state'] == 'Florida']['adjpoll_clinton'], ax = ax,␣
 ↪color='skyblue', label='Clinton')
sns.kdeplot(df[df['state'] == 'Florida']['adjpoll_trump'], ax = ax, color =␣
 ↪'red', label='Trump')
plt.xlabel("Candidate")
plt.title("Trump vs Clinton Florida")
plt.legend()
```

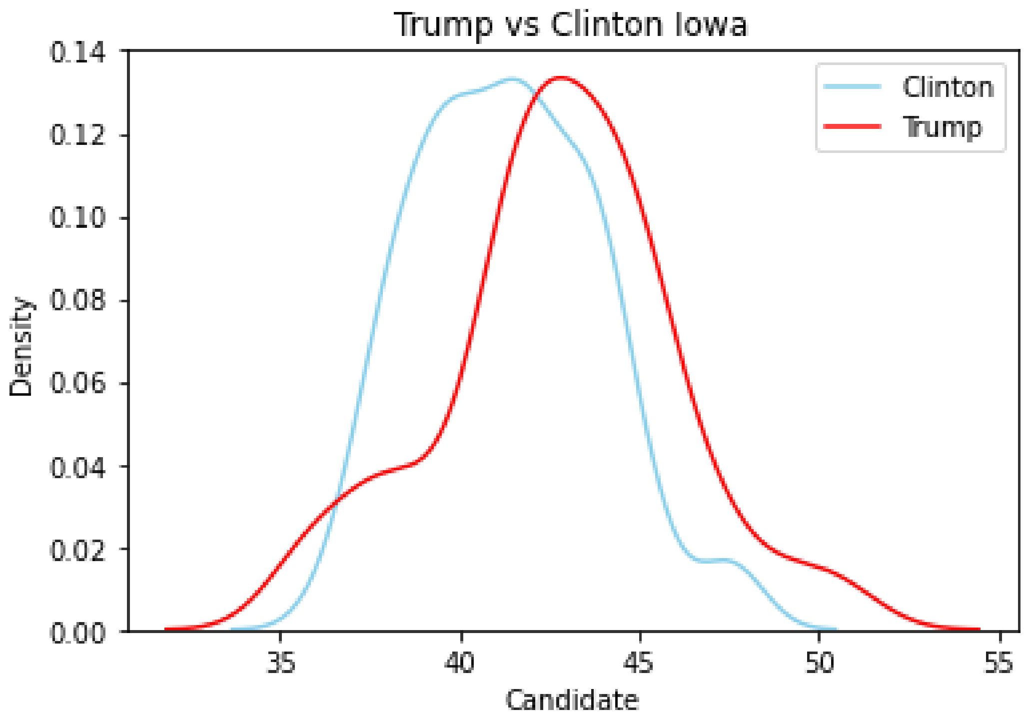
[78]: <matplotlib.legend.Legend at 0x7efb7c0a0c40>



[79]:
```
fig, ax = plt.subplots()
sns.kdeplot(df[df['state'] == 'Iowa']['adjpoll_clinton'], ax = ax,␣
 ↪color='skyblue', label='Clinton')
sns.kdeplot(df[df['state'] == 'Iowa']['adjpoll_trump'], ax = ax, color = 'red',␣
 ↪label='Trump')
plt.xlabel('Candidate')
```

```
plt.title('Trump vs Clinton Iowa')
plt.legend()
```

[79]:
```
<matplotlib.legend.Legend at 0x7efb6cc8edf0>
```



We can see for battleground states even though a state has a higher mode such as Clinton in Florida, Trump in the polls still has the lead as his avergae poll rating is higher. This is most likely due to that Trump has a higher density in Florida giving him a slight lead. Most of the differences come from the distributions being slightly wider or taller in key areas.

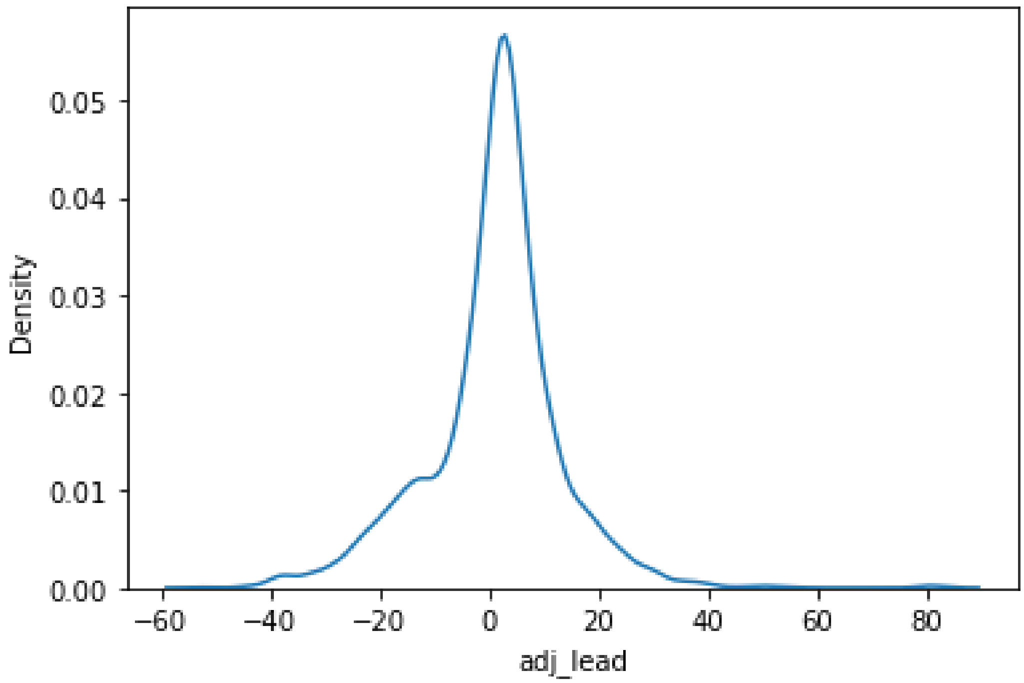
Lets introduce a new variable adjusted lead which will be the difference between Clinton and Trump poll ratings where a positive value means Clinton has a lead over trump and negative means Trump has the lead over Clinton.

[80]:
```
df['adj_lead'] = df['adjpoll_clinton'] - df['adjpoll_trump']

df['adj_lead'].mean(), df['adj_lead'].var()
```

[80]:
```
(0.9762825313599062, 153.4731635576654)
```

[81]:
```
sns.kdeplot(df['adj_lead'])
```

[81]:
```
<AxesSubplot:xlabel='adj_lead', ylabel='Density'>
```



We are trying to construct a prior belief on our estimate for the adjusted lead of the candidate. We will assume that our likelihood follows a normal distribution.

From here we can see the partisan leans for each state and which ones are leaning red or blue. We can see heavy republican leans on the southeast while on the west it seems that leans are much

5 5.0 Bayesian Hierarchial Modeling

5.0.1 Our resarch question will be dealing with trying to estimate the poll leads between Clinton and Trump during the 2016 presidential election. Dataset was taken from https://www.kaggle.com/fivethirtyeight/2016-election-polls

5.1 5.1 Building a Basic Model/Methods

Our graphical model is as follows whre we have our parameter where we have this as our prior belief based on our estimates above.

$\mu \sim Uniform(-40, 40)$

$\sigma^2 \sim HalfNormal(0, 5)$

$X \mid (\mu, \sigma^2) \sim \mathcal{N}(\mu, \sigma^2)$

We choose μ and σ^2 as these priors because we see that most of the values fall between -60 and 60. Finally the variance cannot be negative and the we have a tight distribution so we choose a smaller variance so we choose a half normal.

[82]:
```
import pymc3 as pm
```

```
[83]: with pm.Model() as model:
          = pm.Uniform(' ', lower=-60, upper=60)
          = pm.HalfNormal(' ', sd=5)
        X = pm.Normal('X', mu= , sd= , observed=df['adj_lead'].values)
        trace_guassian = pm.sample(1000, tune=1000, return_inferencedata=True)
```

```
Auto-assigning NUTS sampler…
Initializing NUTS using jitter+adapt_diag…
Multiprocess sampling (4 chains in 4 jobs)
NUTS: [ ,  ]
```

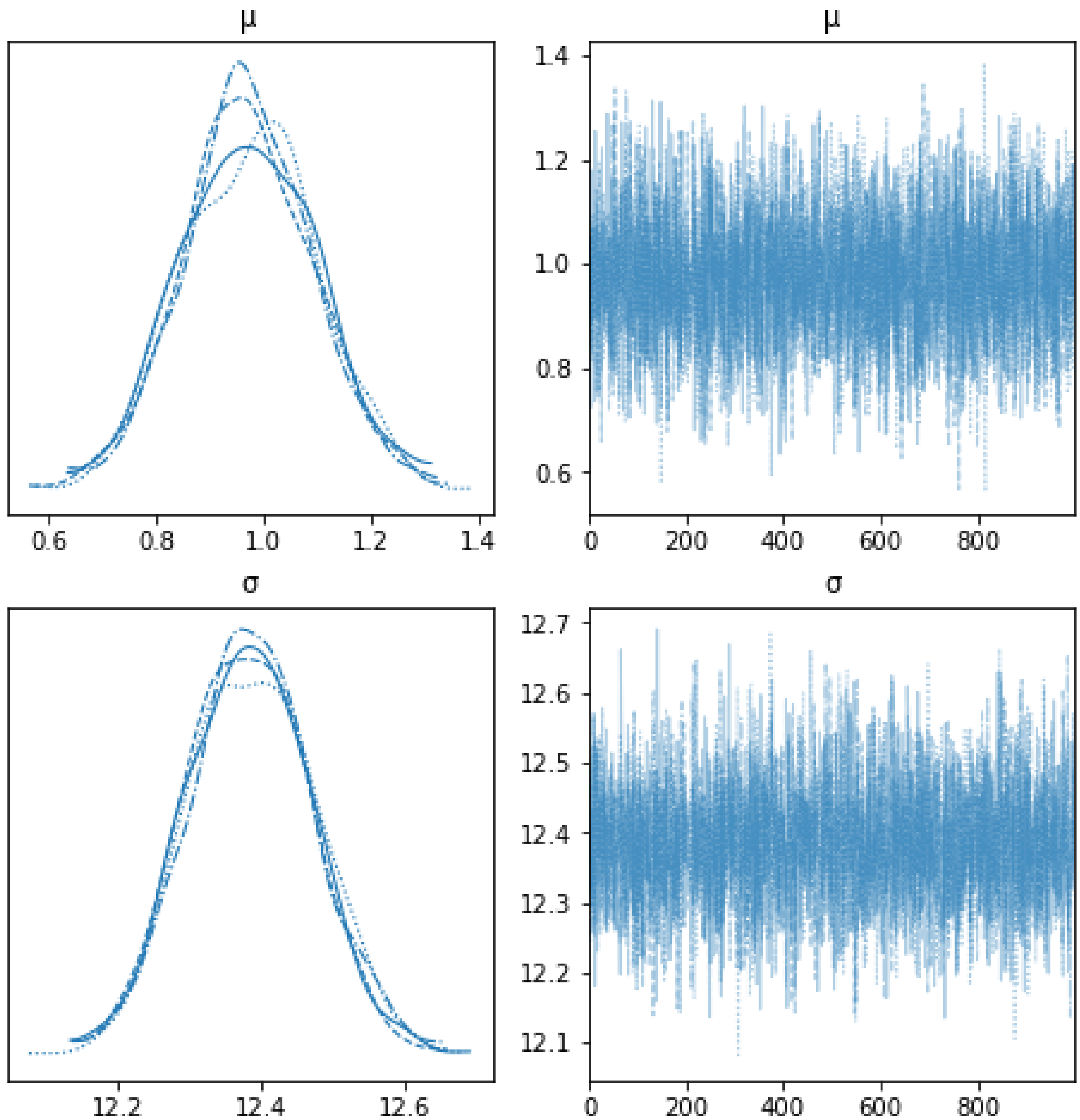
```
<IPython.core.display.HTML object>
```

```
Sampling 4 chains for 1_000 tune and 1_000 draw iterations (4_000 + 4_000 draws
total) took 6 seconds.
```

5.2 5.2 Results

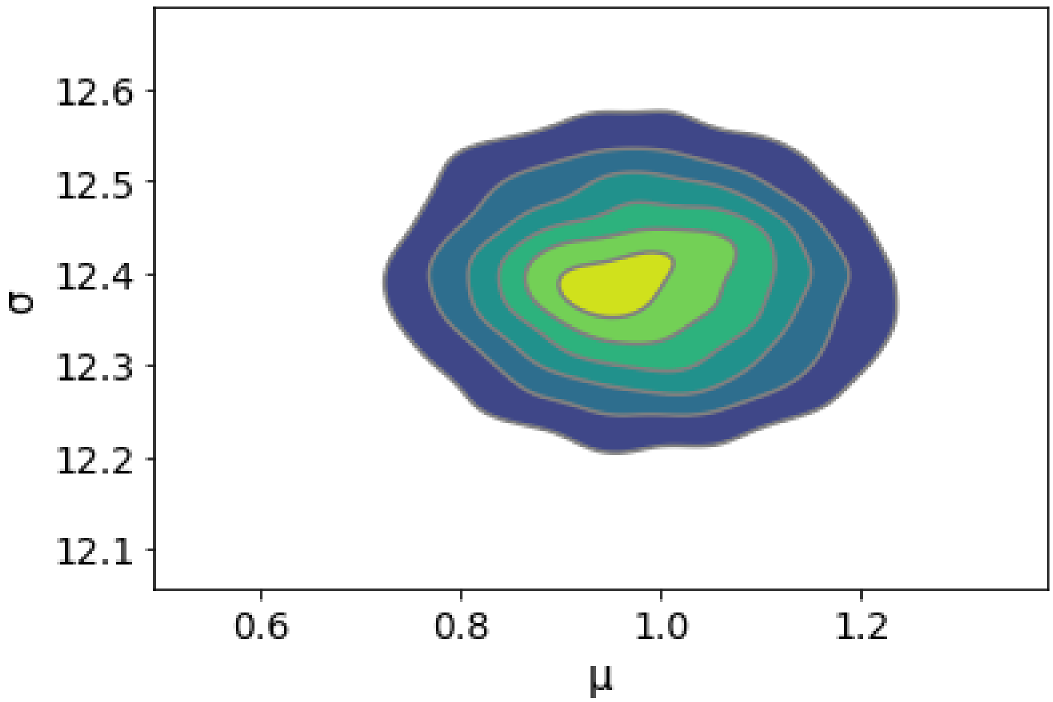
```
[85]: import arviz as az


      f, axs = plt.subplots(2,2,figsize=(8,8))


      az.plot_trace(trace_guassian, axes = axs)
```

```
[85]: array([[<AxesSubplot:title={'center':' '}>,
               <AxesSubplot:title={'center':' '}>],
              [<AxesSubplot:title={'center':' '}>,
               <AxesSubplot:title={'center':' '}>]], dtype=object)
```



Our trace plots look good here. Our values on the left seem to have converged and be stationary and our MAP estimate which is the peak on the left graphs seem to be relatively close to the true value. Lets look at the joint trace of our sample.

[21]:
```
az.plot_pair(trace_guassian, kind='kde', fill_last=False);
```



We can see here that our values do not seem to be correlated with each other which is a good thing. Now lets see if we can categorize the states into groups.

5.3 5.3 Adding Regions to our Model

Lets consider adding the four regions to our model and consider how this changes our model.

[20]:
```
ne = ['Connecticut', 'Maine', 'Massachusetts', 'New Hampshire', 'Rhode Island',
      'Vermont','New Jersey', 'New York', 'Pennsylvania', 'Maine CD-1', 'Maine␣
 ↪CD-2']

mw = ['Illinois','Indiana','Michigan','Ohio', 'Wisconsin','Iowa', 'Kansas',␣
 ↪'Minnesota', 'Missouri',
      'Nebraska', 'North Dakota', 'South Dakota','Nebraska CD-2', 'Nebraska␣
 ↪CD-3', 'Nebraska CD-1']

so= ['Delaware', 'Florida', 'Georgia', 'Maryland', 'North Carolina',
     'South Carolina', 'Virginia', 'District of Columbia', 'West Virginia',
    'Alabama', 'Kentucky', 'Mississippi','Tennessee','Arkansas', 'Louisiana',␣
 ↪'Oklahoma', 'Texas']

we = ['Arizona', 'Colorado', 'Idaho', 'Montana', 'Nevada', 'New Mexico',␣
 ↪'Utah', 'Wyoming',
     'Alaska', 'California', 'Hawaii', 'Oregon', 'Washington']
```

[97]:
```
# U.S randomly considred a state.
df_2 = df.copy()
df_2 = df[df['state'] != 'U.S.']
```

[99]:
```
# Adds a region column to each row which is encoded.
def add_region(row):
    if row['state'] in ne:
        row['region'] = 0
    elif row['state'] in mw:
        row['region'] = 1
    elif row['state'] in so:
        row['region'] = 2
    elif row['state'] in we:
        row['region'] = 3
    return row
```

[98]:
```
# Apply our function we created above.
df_2 = df_2.apply(lambda row: add_region(row), axis= 1)
```

[100]:
```
# Create a index to use in our model.
idx = pd.Categorical(df_2['region'],
                     categories=[0, 1, 2, 3]).codes
```

5.4 5.4 Results of More Robust Model

[32]:
```
with pm.Model() as model_regions:
      = pm.Uniform(' ', lower=-60, upper=60,shape= 4)
      = pm.HalfNormal(' ', sd=5,shape=4)
    X = pm.Normal('X', mu= [idx], sd= [idx], observed=df_2['adj_lead'].values)
    trace_guassian_regions = pm.sample(1000, tune=1000,␣
↪return_inferencedata=False, cores = 1)
```

```
Auto-assigning NUTS sampler…
Initializing NUTS using jitter+adapt_diag…
Sequential sampling (2 chains in 1 job)
NUTS: [ ,  ]
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

```
Sampling 2 chains for 1_000 tune and 1_000 draw iterations (2_000 + 2_000 draws
total) took 14 seconds.
```

[34]:
```
az.summary(az.from_pymc3(trace_guassian_regions))
```

```
Got error No model on context stack. trying to find log_likelihood in
translation.
```

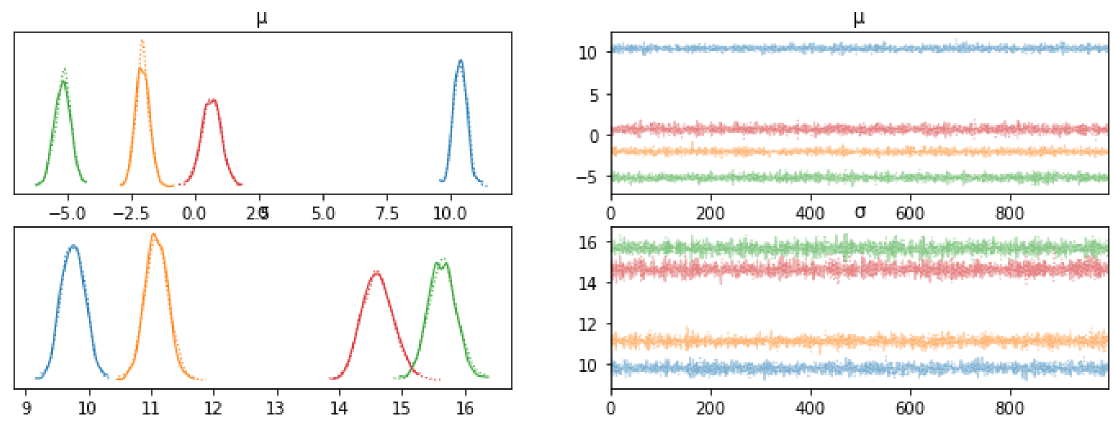
[34]:
```
        mean     sd  hdi_3%  hdi_97%  mcse_mean  mcse_sd  ess_bulk  ess_tail  \
[0]  10.408  0.268   9.906   10.878      0.005    0.003    3228.0    1453.0
[1]  -2.038  0.268  -2.507   -1.498      0.005    0.004    2580.0    1183.0
[2]  -5.155  0.318  -5.752   -4.557      0.006    0.004    2828.0    1611.0
[3]   0.661  0.377  -0.083    1.352      0.006    0.005    3789.0    1608.0
[0]   9.759  0.186   9.406   10.084      0.004    0.002    2790.0    1768.0
[1]  11.088  0.188  10.749   11.456      0.003    0.002    4227.0    1657.0
[2]  15.646  0.227  15.194   16.050      0.004    0.003    3370.0    1694.0
[3]  14.614  0.249  14.189   15.110      0.004    0.003    3630.0    1770.0

     r_hat
[0]    1.0
[1]    1.0
[2]    1.0
[3]    1.0
[0]    1.0
[1]    1.0
[2]    1.0
[3]    1.0
```

From this summary table we can see that there is quite a different in regions. For example the north east seems to have a big lead torwards Hilary Clinton while the midwest and south favor Trump much more.

[77]:
```
az.plot_trace(trace_guassian_regions)
```

```
Got error No model on context stack. trying to find log_likelihood in
translation.
/opt/conda/lib/python3.9/site-packages/arviz/data/io_pymc3_3x.py:98:
FutureWarning: Using `from_pymc3` without the model will be deprecated in a
future release. Not using the model will return less accurate and less useful
results. Make sure you use the model argument or call from_pymc3 within a model
context.
  warnings.warn(
Got error No model on context stack. trying to find log_likelihood in
translation.
```

[77]:
```
array([[<AxesSubplot:title={'center':' '}>,
        <AxesSubplot:title={'center':' '}>],
       [<AxesSubplot:title={'center':' '}>,
        <AxesSubplot:title={'center':' '}>]], dtype=object)
```




```
[78]: df_2.groupby('region').mean()
```

[78]:

region	samplesize	adjpoll_clinton	adjpoll_trump	adj_lead
0	634.572368	47.855455	37.453344	10.402111
1	714.257391	40.852794	42.884180	-2.031386
2	675.943750	41.185942	46.355735	-5.169793
3	606.754128	41.262549	40.590502	0.672047

We see that our model does a good job of being accurate in estimating the means between region. Lets next run a posterior predictive check as model checking is always good.

```
[82]: ppc = pm.sample_posterior_predictive(trace_guassian_regions, samples=2000,␣
      ↪model=model_regions)
```

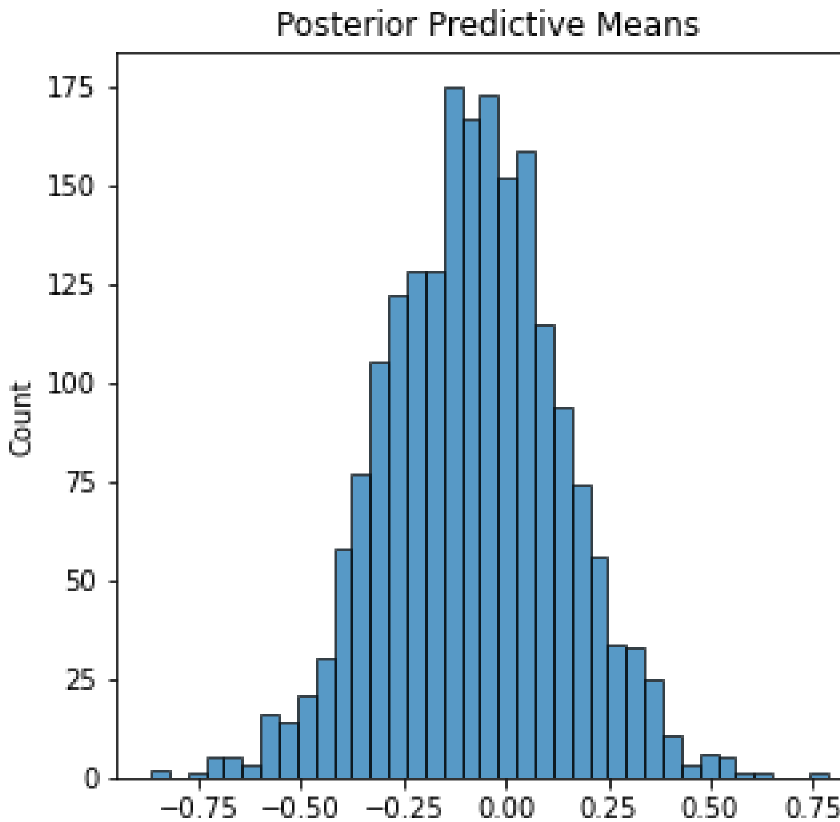
<IPython.core.display.HTML object>

```
[84]: np.asarray(ppc['X']).shape
```

[84]: (2000, 7131)

```
[91]: means = [X.mean() for X in ppc['X']]
      ax = plt.subplots(figsize=(5, 5))
      sns.histplot(means)
      plt.title('Posterior Predictive Means')
```

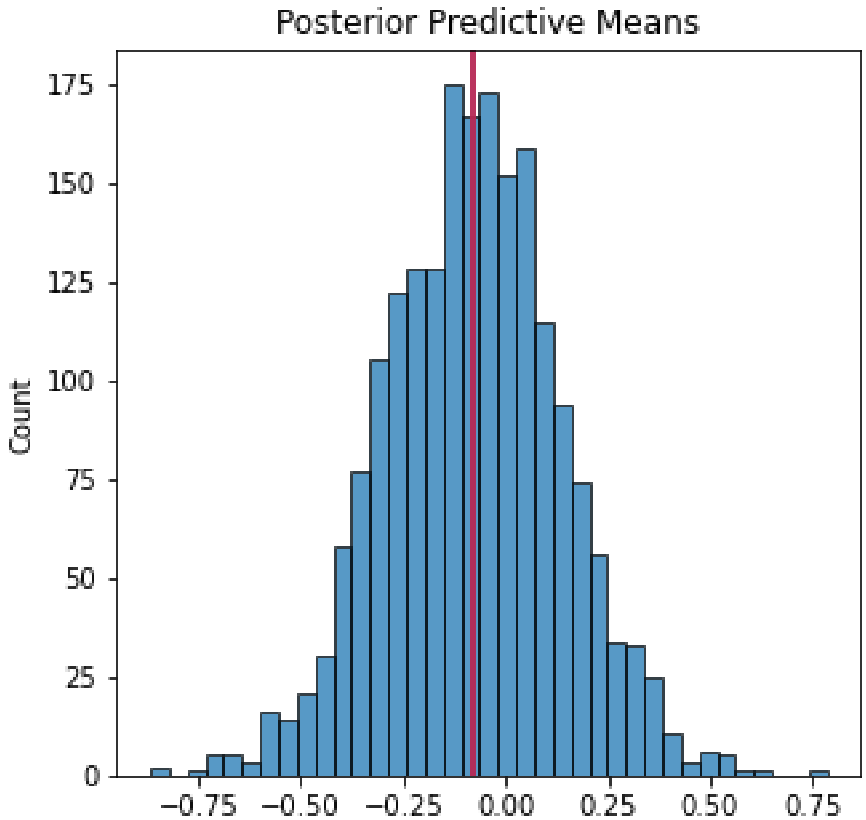
[91]: Text(0.5, 1.0, 'Posterior Predictive Means')



Lets overlay a line of the true mean.

[96]:
```
means = [X.mean() for X in ppc['X']]
ax = plt.subplots(figsize=(5, 5))
sns.histplot(means)
plt.title('Posterior Predictive Means')
ax[1].axvline(df_2['adj_lead'].mean())
plt.axvline(df_2['adj_lead'].mean(), color='crimson')
```

[96]:
```
<matplotlib.lines.Line2D at 0x7fd03efcbb50>
```



We see here that our model does a good job of approximating the mean!

5.5 5.4 Discussion

We began with a simple model where we used our prior beliefs and guassian likelihood functio to approximate the adjust lead which was the difference between the Trump and Clinton poll. We then tried a more robust graphical model where introduced regions and from there saw differences in adjusted leads based on the region. I tried to incorporate poll weight into our graphical model but ran into trouble as I didn't know how the likelihood would cange or maybe the prior I chose for the poll weight was incorrect. This is one of the issues with Bayesian Inference is that you don't quite know how to choose a prior which was the issue I ran into. Some data that would be interesting to look at were the demographics in each region such as gender, race, etc.

[ ]:

```

```