Data 102 Final Project Bayesian Hierarchical Modelling

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1 Bayesian Hierarchical Modeling

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[169]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import pymc3 as pm
```

[170]:
```
with pm.Model() as model:
    dummy = pm.Beta('dummy', alpha=1, beta=1)
    pm.sample(1)
```

```
/var/folders/r2/k7ydhtv97nvfmfl71y382zy40000gn/T/ipykernel_9941/1311453619.py:3:
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.
  pm.sample(1)
Only 1 samples in chain.
Auto-assigning NUTS sampler…
Initializing NUTS using jitter+adapt_diag…
Multiprocess sampling (4 chains in 4 jobs)
NUTS: [dummy]
```

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

```
Sampling 4 chains for 1_000 tune and 1 draw iterations (4_000 + 4 draws total)
took 16 seconds.
/Users/alanjian/opt/anaconda3/envs/pymc3_env/lib/python3.9/site-
packages/arviz/data/base.py:216: UserWarning: More chains (4) than draws (1).
Passed array should have shape (chains, draws, *shape)
  warnings.warn(
/Users/alanjian/opt/anaconda3/envs/pymc3_env/lib/python3.9/site-
packages/pymc3/sampling.py:643: UserWarning: The number of samples is too small
```

```
to check convergence reliably.
  warnings.warn("The number of samples is too small to check convergence
reliably.")
```

2 Data Cleaning

Here, we take a bunch of steps to clean up our data and make it suitable for future work. Here are a series of steps that we took:

2.1 Importing Data

We started by importing the data.

In our study we are interested in the following highly polarized issues. To find these, we highlighted differences in the republican and democratic platforms (links below):

https://democrats.org/where-we-stand/party-platform/

https://prod-cdn-static.gop.com/media/documents/DRAFT_12_FINAL%5B1%5D-ben_1468872234.pdf

https://www2.deloitte.com/us/en/pages/public-sector/articles/top-national-issues.html

Abortion (ABANY): Please tell me whether or not you think it should be possible for a pregnant woman to obtain a legal abortion if the woman wants it for any reason?

Gun Regulation (GUNLAW): Would you favor or oppose a law which would require a person to obtain a police permit before he or she could buy a gun?

Homosexuality (HOMOSEX): What about sexual relations between two adults of the same sex–do you think it is always wrong, almost always wrong, wrong only sometimes, or not wrong at all?

Existence of Racial Discrimination (RACDIF1): On the average (Negroes/Blacks/African-Americans) have worse jobs, income, and housing than white people. Do you think these differences are mainly due to discrimination?

Investment in Environmental Protection (NATENVIR): We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount. Are we spending too much, too little, or about the right amount on improving and protecting the environment?

Investment in National Defense (NATARMS): We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount. Are we spending too much, too little, or about the right amount on national defense?

Investment in Welfare (NATFARE): We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount. Are we spending too much, too little, or about the right amount on Welfare?

Investment in Social Security (NATSOC): We are faced with many problems in this country, none of which can be solved easily or inexpensively. I'm going to name some of these problems, and for each one I'd like you to name some of these problems, and for each one I'd like you to tell me whether you think we're spending too much money on it, too little money, or about the right amount. Are we spending too much, too little, or about the right amount on Social Security

[522]:
```
labels = ['YEAR', 'POLVIEWS', 'ABANY', 'GUNLAW', 'HOMOSEX', 'RACDIF1',␣
↪'NATENVIR', 'NATARMS', 'NATFARE', 'NATSOC']
```

[523]:
```
origlocation = "./GSS/GSS7218_R3"
alanLoc = "~/Downloads/GSS_spss/GSS7218_R3.sav"

pol = pd.read_spss(alanLoc, usecols=labels,
                    convert_categoricals=True)
```

2.2 Initial Transformations

Additionally, we make some further modifications, chopping off any data prior to 2000s (because we're interested in the period between 2000-2018).

[524]:
```
pol = pol[pol['YEAR'] >= 2000]
pol
```

[524]:
```
         YEAR              POLVIEWS     NATENVIR      NATARMS      NATFARE  \
38116  2000.0  SLGHTLY CONSERVATIVE   TOO LITTLE     TOO MUCH     TOO MUCH
38117  2000.0          CONSERVATIVE          NaN          NaN          NaN
38118  2000.0          CONSERVATIVE   TOO LITTLE   TOO LITTLE  ABOUT RIGHT
38119  2000.0  SLGHTLY CONSERVATIVE   TOO LITTLE     TOO MUCH     TOO MUCH
38120  2000.0      SLIGHTLY LIBERAL          NaN          NaN          NaN
…        …                    …           …            …           …
64809  2018.0              MODERATE   TOO LITTLE  ABOUT RIGHT   TOO LITTLE
64810  2018.0  SLGHTLY CONSERVATIVE  ABOUT RIGHT  ABOUT RIGHT  ABOUT RIGHT
64811  2018.0              MODERATE          NaN          NaN          NaN
64812  2018.0          CONSERVATIVE  ABOUT RIGHT   TOO LITTLE     TOO MUCH
64813  2018.0                   NaN          NaN          NaN          NaN

            NATSOC  GUNLAW ABANY           HOMOSEX RACDIF1
38116   TOO LITTLE  OPPOSE    NO  NOT WRONG AT ALL      NO
38117   TOO LITTLE   FAVOR    NO               NaN     NaN
38118  ABOUT RIGHT     NaN   NaN               NaN      NO
38119   TOO LITTLE     NaN   NaN               NaN      NO
38120  ABOUT RIGHT     NaN   NaN               NaN      NO
…             …      …     …                …       …
64809  ABOUT RIGHT  OPPOSE   YES  NOT WRONG AT ALL     YES
64810   TOO LITTLE  OPPOSE    NO               NaN      NO
```

```
64811  ABOUT RIGHT   FAVOR    NO  NOT WRONG AT ALL     NaN
64812   TOO LITTLE     NaN   NaN               NaN      NO
64813   TOO LITTLE   FAVOR    NO               NaN     NaN

[26698 rows x 10 columns]
```

Since we're most interested in political viewpoint, and it was asked of everyone, we will remove individuals who did not respond, since updates that correspond with those data are not informative.

[525]:
```python
pol = pol[~pol['POLVIEWS'].isna()]
pol
```

[525]:
```
         YEAR              POLVIEWS     NATENVIR      NATARMS      NATFARE  \
38116  2000.0  SLGHTLY CONSERVATIVE   TOO LITTLE     TOO MUCH     TOO MUCH
38117  2000.0          CONSERVATIVE          NaN          NaN          NaN
38118  2000.0          CONSERVATIVE   TOO LITTLE   TOO LITTLE  ABOUT RIGHT
38119  2000.0  SLGHTLY CONSERVATIVE   TOO LITTLE     TOO MUCH     TOO MUCH
38120  2000.0      SLIGHTLY LIBERAL          NaN          NaN          NaN
…       …                     …            …            …          …
64808  2018.0              MODERATE  ABOUT RIGHT  ABOUT RIGHT     TOO MUCH
64809  2018.0              MODERATE   TOO LITTLE  ABOUT RIGHT   TOO LITTLE
64810  2018.0  SLGHTLY CONSERVATIVE  ABOUT RIGHT  ABOUT RIGHT  ABOUT RIGHT
64811  2018.0              MODERATE          NaN          NaN          NaN
64812  2018.0          CONSERVATIVE  ABOUT RIGHT   TOO LITTLE     TOO MUCH

            NATSOC  GUNLAW ABANY           HOMOSEX RACDIF1
38116   TOO LITTLE  OPPOSE    NO  NOT WRONG AT ALL      NO
38117   TOO LITTLE   FAVOR    NO               NaN     NaN
38118  ABOUT RIGHT     NaN   NaN               NaN      NO
38119   TOO LITTLE     NaN   NaN               NaN      NO
38120  ABOUT RIGHT     NaN   NaN               NaN      NO
…              …     …     …                 …     …
64808   TOO LITTLE   FAVOR    NO   SOMETIMES WRONG     NaN
64809  ABOUT RIGHT  OPPOSE   YES  NOT WRONG AT ALL     YES
64810   TOO LITTLE  OPPOSE    NO               NaN      NO
64811  ABOUT RIGHT   FAVOR    NO  NOT WRONG AT ALL     NaN
64812   TOO LITTLE     NaN   NaN               NaN      NO

[22849 rows x 10 columns]
```

[526]:
```python
# sanity check to make sure we're including all the right years.
sorted(causal['YEAR'].value_counts().index)
```

[526]:
```
[2000.0,
 2002.0,
 2004.0,
 2006.0,
```

```
 2008.0,
 2010.0,
 2012.0,
 2014.0,
 2016.0,
 2018.0]
```

When comparing the data from the GSS data explorer and our extracted data, it looks like NaN values are comprised of three different types of users: 1. **Declined to Respond**: They did not respond to the prompt 2. **Don't Know**: They did not know enough about the subject to respond 3. **Not Applicable:** They were not asked the prompt

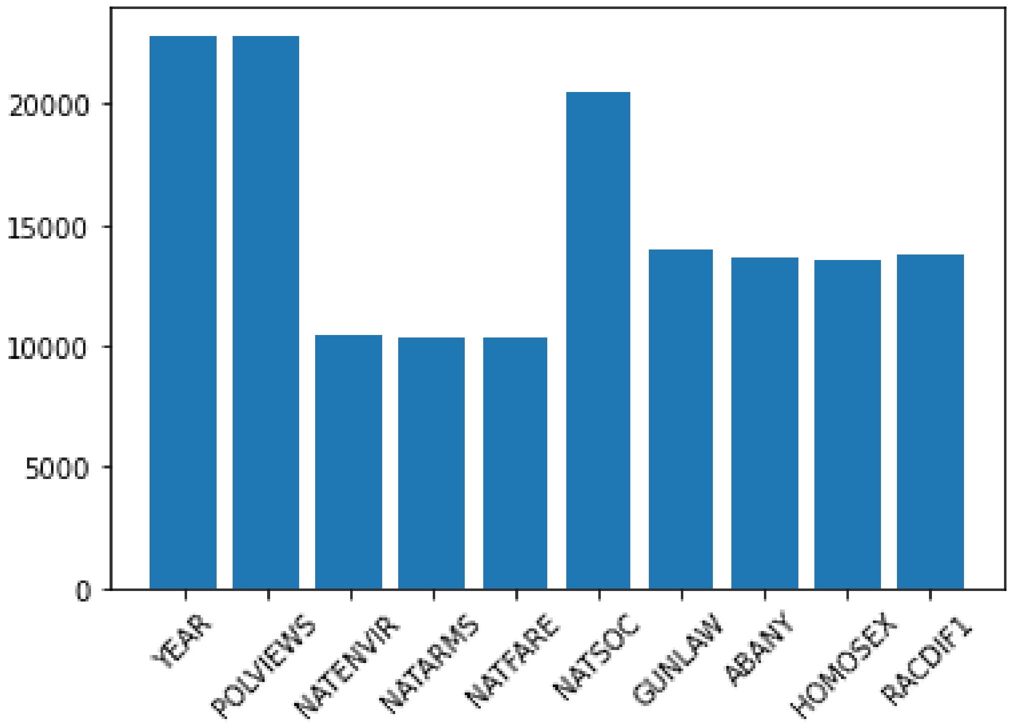
[527]:
```
pol[['POLVIEWS']].isna().groupby('POLVIEWS').size()
```

[527]:
```
POLVIEWS
False    22849
dtype: int64
```

An overwhelming majority of these NaNs are comprised of those who were never asked the question (>95%), so we can safely assume that they are missing completely at random (MCAR).

We can also see that, with a total size of 27000 respondents, a majority of these questions were only asked to roughly half of the individuals in the study, with the exception of self-reported political leaning, and opinion of investment in social security.

[528]:
```
num_responses = np.sum(~pol.isna(), axis=0)
plt.bar(num_responses.index, num_responses)
plt.xticks(rotation=45);
```



3 Binarizing Variables

In order for our study to match the design of our bayesian hierarchical model, we will have to binarize all of the questions that feature multiple values.

As a result, these variables and their interpretation will be changed in the following way: 1. **Homosexuality** (HOMOSEX): What about sexual relations between two adults of the same sex– do you think it is wrong at all? 2. **Gender Discrimination in the Workplace** (DISCAFF): Do you think that it's likely these days that a woman won't get a job or promotion while an equally or less qualified man gets one instead? 4. **Investment in Environmental Protection** (NATENVIR): Do we need to spend more on protecting the environment? 5. **Investment in National Defense** (NATARMS): Do we need to spend more on national defense? 6. **Investment in Welfare** (NATFARE): Do we need to spend more on welfare? 7. **Investment in Social Security** (NATSOC): Do we need to spend more on social security?

Additionally, since PyMC3 works with numerical values, we'll also have to binarize: 1. **Abortion** (ABANY) 2. **Existence of Racial Discrimination** (RACDIF1) 3. **Gun Regulation** (GUNLAW)

[529]:
```
binarized = pol.copy()
```

3.0.1 Homosexuality

[530]:
```
pol['HOMOSEX'].value_counts()
```

[530]:
```
ALWAYS WRONG        6354
NOT WRONG AT ALL    5673
SOMETIMES WRONG      949
ALMST ALWAYS WRG     546
OTHER                  0
Name: HOMOSEX, dtype: int64
```

[531]:
```
pd.get_dummies(pol[['HOMOSEX']]).columns
```

[531]:
```
Index(['HOMOSEX_ALMST ALWAYS WRG', 'HOMOSEX_ALWAYS WRONG',
       'HOMOSEX_NOT WRONG AT ALL', 'HOMOSEX_OTHER', 'HOMOSEX_SOMETIMES WRONG'],
      dtype='object')
```

[532]:
```
# Find individuals who think homosexuality is wrong
homosex = pd.get_dummies(pol[['HOMOSEX']])[['HOMOSEX_ALMST ALWAYS WRG',
                                            'HOMOSEX_ALWAYS WRONG',
                                            'HOMOSEX_SOMETIMES WRONG']]
homo_bool = np.sum(homosex, axis=1)

#Re-identify those who did not answer the question
homo_bool.iloc[pol['HOMOSEX'].isna().to_list()] = np.nan

binarized['HOMOSEX'] = homo_bool
homo_bool
```

[532]:
```
38116    0.0
38117    NaN
38118    NaN
38119    NaN
38120    NaN
        …
64808    1.0
64809    0.0
64810    NaN
64811    0.0
64812    NaN
Length: 22849, dtype: float64
```

3.0.2 Gender Discrimination in the Workplace

[499]:
```
"""# Find individuals who think gender discrimination is likely to occur even␣
↪today
pol['DISCAFFW'].value_counts()"""
```

[499]:
```
SOMEWHAT LIKELY      3298
VERY LIKELY          1655
SOMEWHAT UNLIKELY    1292
VERY UNLIKELY         586
Name: DISCAFFW, dtype: int64
```

[533]:
```
"""discaffw = pd.get_dummies(pol[['DISCAFFW']])[['DISCAFFW_SOMEWHAT LIKELY',
                                              'DISCAFFW_VERY LIKELY']]

discaffw_bool = np.sum(discaffw, axis=1)

#Re-identify those who did not answer the question
discaffw_bool.iloc[pol['DISCAFFW'].isna().to_list()] = np.nan

binarized['DISCAFFW'] = discaffw_bool
discaffw_bool"""
```

[533]:
```
"discaffw = pd.get_dummies(pol[['DISCAFFW']])[['DISCAFFW_SOMEWHAT LIKELY',\n
'DISCAFFW_VERY LIKELY']]\n\ndiscaffw_bool = np.sum(discaffw, axis=1)\n\n#Re-
identify those who did not answer the
question\ndiscaffw_bool.iloc[pol['DISCAFFW'].isna().to_list()] =
np.nan\n\nbinarized['DISCAFFW'] = discaffw_bool\ndiscaffw_bool"
```

3.0.3 Investment in Environmental Protection

[534]:
```
pol['NATENVIR'].value_counts()
```

[534]:
```
TOO LITTLE     6580
ABOUT RIGHT    2975
TOO MUCH        885
Name: NATENVIR, dtype: int64
```

[535]:
```
# Find individuals who think we aren't spending enough on climate change and␣
↪preserving environment
natenvir_bool = pd.get_dummies(pol[['NATENVIR']])[['NATENVIR_TOO LITTLE']]

#Re-identify those who did not answer the question
natenvir_bool.iloc[pol['NATENVIR'].isna().to_list()] = np.nan

binarized['NATENVIR'] = natenvir_bool
natenvir_bool
```

[535]:
```
       NATENVIR_TOO LITTLE
38116                  1.0
38117                  NaN
38118                  1.0
38119                  1.0
38120                  NaN
…                    …
64808                  0.0
64809                  1.0
64810                  0.0
64811                  NaN
64812                  0.0

[22849 rows x 1 columns]
```

3.0.4 Investment in National Defense

[536]:
```
pol['NATARMS'].value_counts()
```

[536]:
```
ABOUT RIGHT    3988
TOO MUCH       3278
TOO LITTLE     3107
Name: NATARMS, dtype: int64
```

[537]:
```
# Find individuals who think we aren't spending enough on national defense and␣
↪army
natarms_bool = pd.get_dummies(pol[['NATARMS']])[['NATARMS_TOO LITTLE']]

# Re-identify those who did not answer the question
natarms_bool.iloc[pol['NATARMS'].isna().to_list()] = np.nan

binarized['NATARMS'] = natarms_bool
natarms_bool
```

[537]:
```
       NATARMS_TOO LITTLE
38116                 0.0
38117                 NaN
38118                 1.0
38119                 0.0
38120                 NaN
…                   …
64808                 0.0
64809                 0.0
64810                 0.0
64811                 NaN
64812                 1.0
```

```
[22849 rows x 1 columns]
```

3.0.5 Investment in Welfare

[538]:
```python
natfare_bool = pd.get_dummies(pol[['NATFARE']])[['NATFARE_TOO LITTLE']]

# Re-identify those who did not answer the question
natfare_bool.iloc[pol['NATFARE'].isna().to_list()] = np.nan

binarized['NATFARE'] = natfare_bool
natfare_bool
```

[538]:
```
       NATFARE_TOO LITTLE
38116                 0.0
38117                 NaN
38118                 0.0
38119                 0.0
38120                 NaN
…                   …
64808                 0.0
64809                 1.0
64810                 0.0
64811                 NaN
64812                 0.0

[22849 rows x 1 columns]
```

3.0.6 Investment in Social Security

[539]:
```python
natsoc_bool = pd.get_dummies(pol[['NATSOC']])[['NATSOC_TOO LITTLE']]

# Re-identify those who did not answer the question
natsoc_bool.iloc[pol['NATSOC'].isna().to_list()] = np.nan

binarized['NATSOC'] = natsoc_bool
natsoc_bool
```

[539]:
```
       NATSOC_TOO LITTLE
38116                1.0
38117                1.0
38118                0.0
38119                1.0
38120                0.0
…                  …
64808                1.0
64809                0.0
```

```
64810                 1.0
64811                 0.0
64812                 1.0

[22849 rows x 1 columns]
```

3.0.7 Opinion on Gun Regulation

[540]:
```
pol[['GUNLAW']].value_counts()
```

[540]:
```
GUNLAW
FAVOR     10679
OPPOSE     3339
dtype: int64
```

[541]:
```
gunlaw_bool = pd.get_dummies(pol[['GUNLAW']])[['GUNLAW_FAVOR']]

#Re-identify those who did not answer the question
gunlaw_bool.iloc[pol['GUNLAW'].isna().to_list()] = np.nan

binarized['GUNLAW'] = gunlaw_bool
gunlaw_bool
```

[541]:
```
       GUNLAW_FAVOR
38116           0.0
38117           1.0
38118           NaN
38119           NaN
38120           NaN
…             …
64808           1.0
64809           0.0
64810           0.0
64811           1.0
64812           NaN

[22849 rows x 1 columns]
```

3.0.8 Opinion on Abortion

[542]:
```
pol[['ABANY']].value_counts()
```

[542]:
```
ABANY
NO       7640
YES      6052
dtype: int64
```

[543]:
```
abany_bool = pd.get_dummies(pol[['ABANY']])[['ABANY_YES']]

#Re-identify those who did not answer the question
abany_bool.iloc[pol['ABANY'].isna().to_list()] = np.nan

binarized['ABANY'] = abany_bool
abany_bool
```

[543]:
```
       ABANY_YES
38116        0.0
38117        0.0
38118        NaN
38119        NaN
38120        NaN
…            …
64808        0.0
64809        1.0
64810        0.0
64811        0.0
64812        NaN

[22849 rows x 1 columns]
```

3.0.9 Opinion on Racial Discrimination

[544]:
```
pol[['ABANY']].value_counts()
```

[544]:
```
ABANY
NO       7640
YES      6052
dtype: int64
```

[545]:
```
racdif1_bool = pd.get_dummies(pol[['RACDIF1']])[['RACDIF1_YES']]

#Re-identify those who did not answer the question
racdif1_bool.iloc[pol['RACDIF1'].isna().to_list()] = np.nan

binarized['RACDIF1'] = racdif1_bool
racdif1_bool
```

[545]:
```
       RACDIF1_YES
38116          0.0
38117          NaN
38118          0.0
38119          0.0
38120          0.0
…              …
```

```
64808          NaN
64809          1.0
64810          0.0
64811          NaN
64812          0.0

[22849 rows x 1 columns]
```

4 Centering and Reorganizing POLVIEWS

As per Ramesh's suggestion, we're centering `POLVIEWS` at 0, so that the sign of the variable is informative in whether or not someone is conservative or liberal.

[546]:
```
pol[['POLVIEWS']].value_counts()
```

[546]:
```
POLVIEWS
MODERATE                8831
CONSERVATIVE            3601
SLGHTLY CONSERVATIVE    3231
LIBERAL                 2770
SLIGHTLY LIBERAL        2604
EXTREMELY LIBERAL        917
EXTRMLY CONSERVATIVE     895
dtype: int64
```

[547]:
```
neg_three = pol[['POLVIEWS']] == 'EXTREMELY LIBERAL'
neg_two = pol[['POLVIEWS']] == 'LIBERAL'
neg_one = pol[['POLVIEWS']] == 'SLIGHTLY LIBERAL'
zero = pol[['POLVIEWS']] == 'MODERATE'
one = pol[['POLVIEWS']] == 'SLGHTLY CONSERVATIVE'
two = pol[['POLVIEWS']] == 'CONSERVATIVE'
three = pol[['POLVIEWS']] == 'EXTRMLY CONSERVATIVE'
```

[548]:
```
polviews = -3 * neg_three + -2 * neg_two + -1 * neg_one + 0 * zero + 1 * one +␣
↪2 * two + 3 * three
binarized['POLVIEWS'] = polviews
polviews
```

[548]:
```
       POLVIEWS
38116         1
38117         2
38118         2
38119         1
38120        -1
…           …
64808         0
64809         0
```

```
64810         1
64811         0
64812         2

[22849 rows x 1 columns]
```

5 Cleaned Data Ready for Use!

[549]:
```python
clean_data = binarized.copy()
clean_data.head()
```

[549]:
```
        YEAR  POLVIEWS  NATENVIR  NATARMS  NATFARE  NATSOC  GUNLAW  ABANY  \
38116  2000.0         1       1.0      0.0      0.0     1.0     0.0    0.0
38117  2000.0         2       NaN      NaN      NaN     1.0     1.0    0.0
38118  2000.0         2       1.0      1.0      0.0     0.0     NaN    NaN
38119  2000.0         1       1.0      0.0      0.0     1.0     NaN    NaN
38120  2000.0        -1       NaN      NaN      NaN     0.0     NaN    NaN

       HOMOSEX  RACDIF1
38116      0.0      0.0
38117      NaN      NaN
38118      NaN      0.0
38119      NaN      0.0
38120      NaN      0.0
```

6 Notes on Value Imputation

Like I said before, our data is MCAR, so it stands that we could just use automatic imputation as implemented by PyMC3. In order to do this, we literally do nothing; PyMC3 will automatically do the imputation once it sees NaN values (source: https://discourse.pymc.io/t/missing-values-in-a-model/2157/9).

Logically, this imputation will not affect our update to the prior, since it is treated as an unseen random variable with a prior that can be updated just like any other random variable.

7 Yeet

Let's do this thing!

[550]:
```python
test = clean_data.dropna()
test
```

[550]:
```
        YEAR  POLVIEWS  NATENVIR  NATARMS  NATFARE  NATSOC  GUNLAW  ABANY  \
38116  2000.0         1       1.0      0.0      0.0     1.0     0.0    0.0
38122  2000.0         0       1.0      0.0      0.0     0.0     0.0    0.0
38137  2000.0         0       1.0      0.0      0.0     1.0     1.0    1.0
```

```
38138  2000.0       -1      1.0      0.0      0.0     0.0     1.0    0.0
38139  2000.0        2      0.0      0.0      0.0     0.0     0.0    1.0
…        …      …       …       …       …      …       …      …
64786  2018.0       -3      1.0      0.0      0.0     1.0     1.0    1.0
64791  2018.0       -2      1.0      0.0      1.0     1.0     0.0    1.0
64799  2018.0        0      1.0      0.0      0.0     0.0     0.0    1.0
64805  2018.0        0      1.0      0.0      0.0     0.0     1.0    1.0
64809  2018.0        0      1.0      0.0      1.0     0.0     0.0    1.0

       HOMOSEX  RACDIF1
38116      0.0      0.0
38122      1.0      0.0
38137      1.0      0.0
38138      1.0      0.0
38139      1.0      0.0
…          …      …
64786      0.0      1.0
64791      0.0      1.0
64799      0.0      1.0
64805      0.0      1.0
64809      0.0      1.0

[2866 rows x 10 columns]
```

[551]:
```python
#questions = clean_data.columns[2:]
questions = test.columns[2:]
questions
```

[551]:
```
Index(['NATENVIR', 'NATARMS', 'NATFARE', 'NATSOC', 'GUNLAW', 'ABANY',
       'HOMOSEX', 'RACDIF1'],
      dtype='object')
```

[552]:
```python
import theano.tensor as tt
```

[631]:
```python
with pm.Model() as model:

    eps = pm.Normal('eps', 0, 0.025)
    beta_vector = pm.Flat('beta', shape=(len(questions), 1))
    noisy = test['POLVIEWS'].to_numpy() + eps
    p = pm.math.sigmoid(tt.outer(noisy, beta_vector))
    pm.Bernoulli('ys', p=p, observed=test[questions])

    trace = pm.sample(500, tune=2000)
```

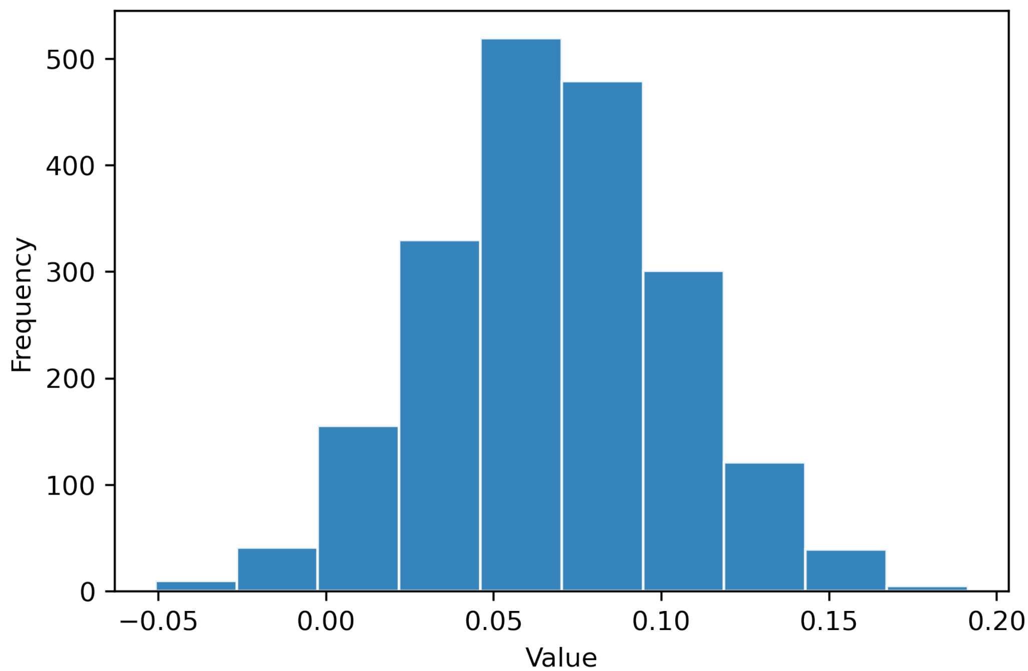
```
/var/folders/r2/k7ydhtv97nvfmfl71y382zy40000gn/T/ipykernel_9941/2085958981.py:9:
FutureWarning: In v4.0, pm.sample will return an `arviz.InferenceData` object
instead of a `MultiTrace` by default. You can pass return_inferencedata=True or
```

```
return_inferencedata=False to be safe and silence this warning.
  trace = pm.sample(500, tune=2000)
Auto-assigning NUTS sampler…
Initializing NUTS using jitter+adapt_diag…
Multiprocess sampling (4 chains in 4 jobs)
NUTS: [beta, eps]
```

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

```
Sampling 4 chains for 2_000 tune and 500 draw iterations (8_000 + 2_000 draws
total) took 97 seconds.
```

[658]:
```
plt.figure(dpi=300)
plt.hist(trace['eps'], ec='w', alpha=0.9)
plt.xlabel("Value")
plt.ylabel("Frequency");
plt.savefig("/Users/alanjian/Desktop/Data 102/Posterior of Eps")
```



[648]:
```
# Concentration inequality
np.mean(trace['eps'] >= 0)
```

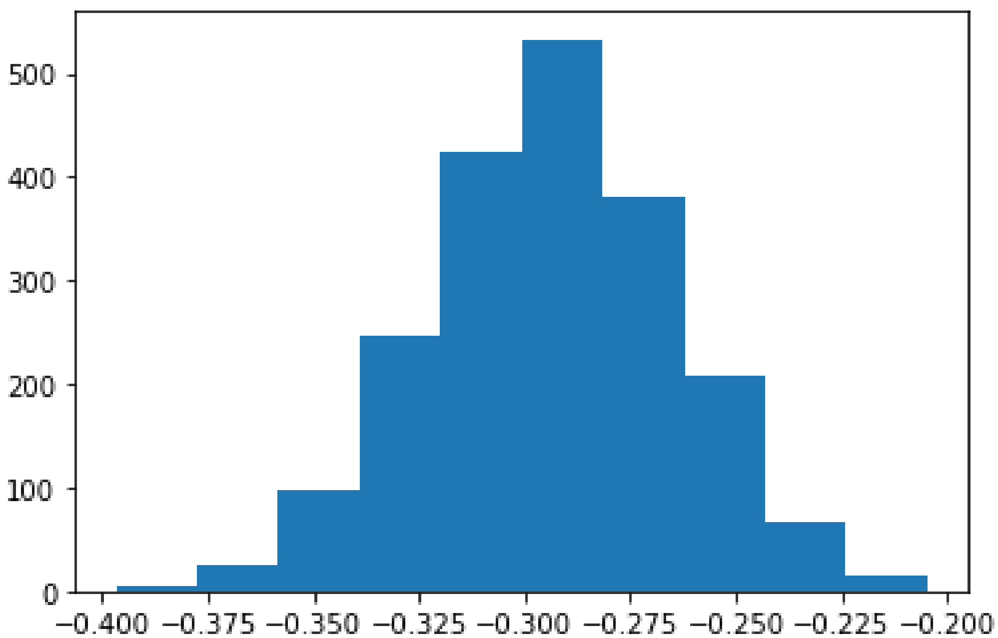
[648]: 0.97

[788]:
```
np.mean(trace['eps'])
```

[788]: 0.06813629620390414

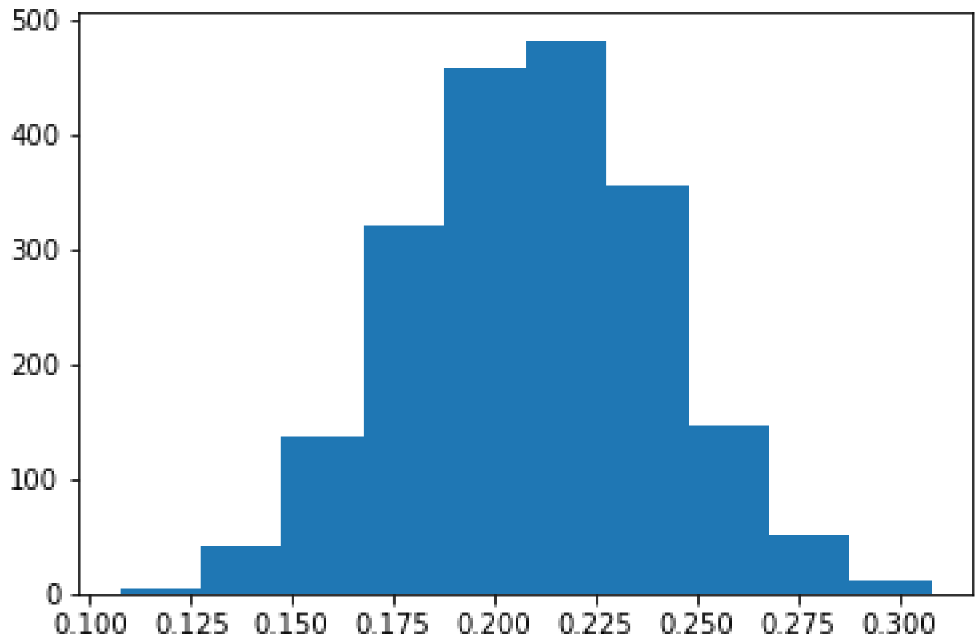
[636]:
```
#NATENVIR
plt.figure(dpi=300)
plt.hist(trace['beta'][:, 0], ec='w', alpha=0.9)
plt.xlabel("Value")
plt.ylabel("Frequency");
plt.savefig("/Users/alanjian/Desktop/Data 102/Posterior of Eps")
```

[636]:
```
(array([  5.,  24.,  98., 246., 424., 533., 381., 208.,  66.,  15.]),
 array([-0.39674304, -0.37752905, -0.35831507, -0.33910108, -0.3198871 ,
        -0.30067311, -0.28145913, -0.26224514, -0.24303116, -0.22381717,
        -0.20460319]),
 <BarContainer object of 10 artists>)
```



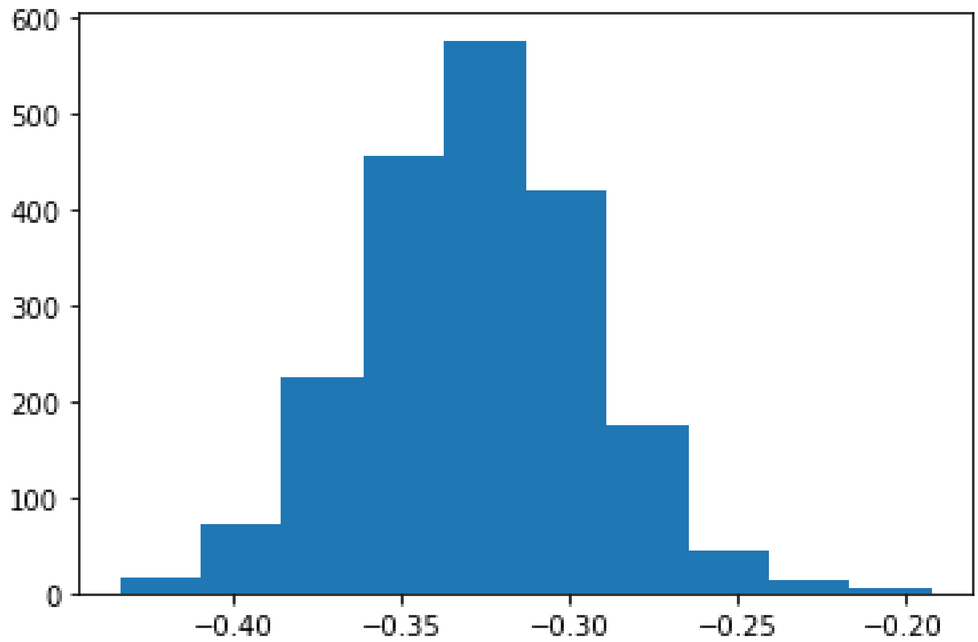
[637]:
```
#NATARMS
plt.figure(dpi=300)
plt.hist(trace['beta'][:, 1], ec='w', alpha=0.9)
```

[637]:
```
(array([  5.,  41., 136., 320., 457., 481., 354., 145.,  50.,  11.]),
 array([0.10736056, 0.12742431, 0.14748806, 0.16755181, 0.18761556,
        0.20767931, 0.22774306, 0.24780681, 0.26787056, 0.28793431,
        0.30799806]),
 <BarContainer object of 10 artists>)
```



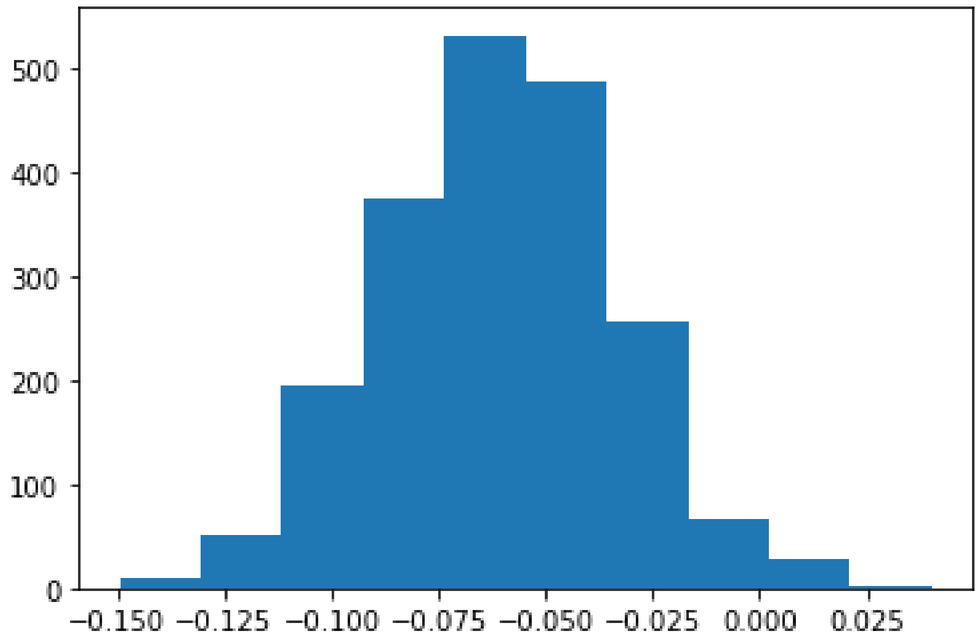
[638]:
```
#NATFARE
plt.figure(dpi=300)
plt.hist(trace['beta'][:, 2], ec='w', alpha=0.9)
```

[638]:
```
(array([ 15.,  72., 225., 456., 577., 419., 176.,  44.,  12.,   4.]),
 array([-0.43376586, -0.40957713, -0.38538841, -0.36119968, -0.33701095,
        -0.31282222, -0.28863349, -0.26444477, -0.24025604, -0.21606731,
        -0.19187858]),
 <BarContainer object of 10 artists>)
```



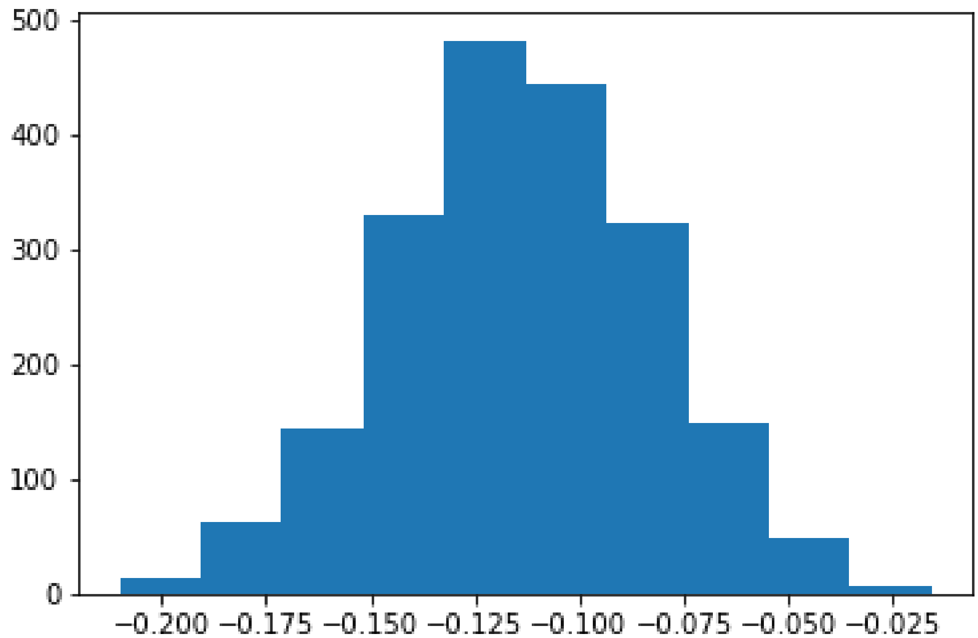
[639]:
```
#NATSOC
plt.figure(dpi=300)
plt.hist(trace['beta'][:, 3], ec='w', alpha=0.9)
```

[639]:
```
(array([  9.,  50., 195., 374., 532., 488., 256.,  67.,  28.,   1.]),
 array([-0.14951508, -0.13054542, -0.11157575, -0.09260608, -0.07363642,
        -0.05466675, -0.03569708, -0.01672741,  0.00224225,  0.02121192,
         0.04018159]),
 <BarContainer object of 10 artists>)
```



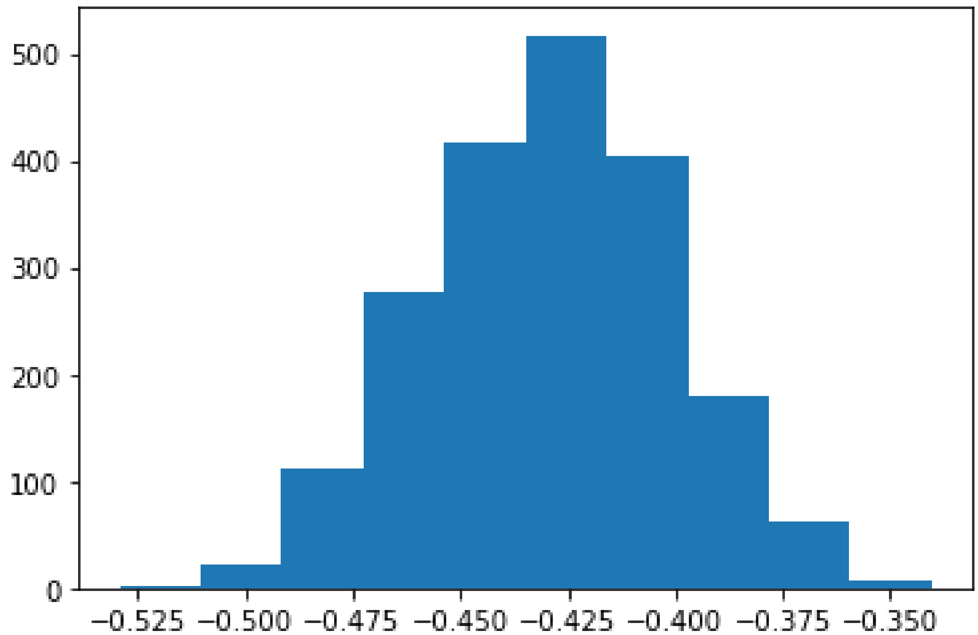
[640]:
```
#GUNLAW
plt.figure(dpi=300)
plt.hist(trace['beta'][:, 4], ec='w', alpha=0.9)
```

[640]:
```
(array([ 14.,  63., 143., 330., 482., 443., 322., 148.,  48.,   7.]),
 array([-0.21006821, -0.19063603, -0.17120386, -0.15177168, -0.13233951,
        -0.11290733, -0.09347516, -0.07404298, -0.05461081, -0.03517863,
        -0.01574646]),
 <BarContainer object of 10 artists>)
```



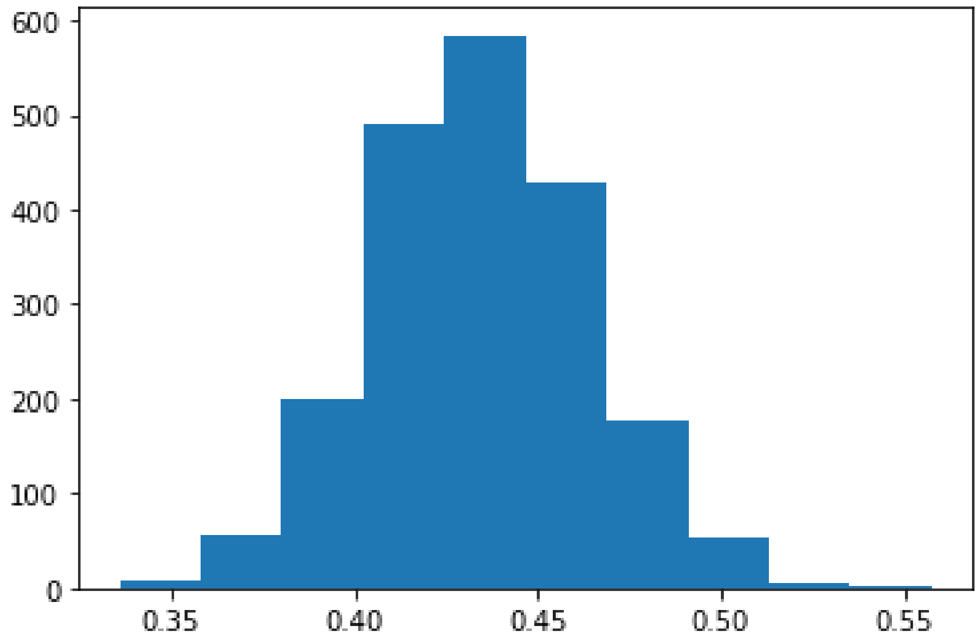
[641]:
```
#ABANY
plt.figure(dpi=300)
plt.hist(trace['beta'][:, 5], ec='w', alpha=0.9)
```

[641]:
```
(array([  3.,  22., 113., 277., 416., 517., 404., 180.,  61.,   7.]),
 array([-0.52919035, -0.51031159, -0.49143283, -0.47255407, -0.45367531,
        -0.43479655, -0.41591779, -0.39703903, -0.37816027, -0.35928151,
        -0.34040275]),
 <BarContainer object of 10 artists>)
```



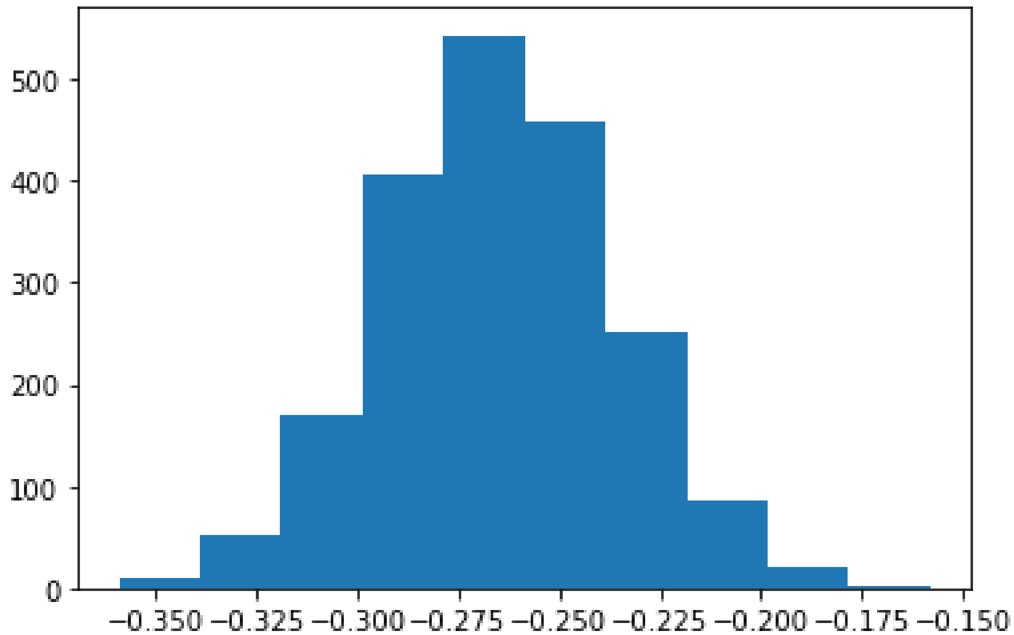
[642]:
```
#HOMOSEX (I defined it in the inverse; Do you think Homosexual relations are␣
↪wrong?)
plt.figure(dpi=300)
plt.hist(trace['beta'][:, 6], ec='w', alpha=0.9)
```

[642]:
```
(array([  7.,  56., 201., 489., 584., 427., 177.,  53.,   5.,   1.]),
 array([0.33579566, 0.35796155, 0.38012744, 0.40229333, 0.42445921,
        0.4466251 , 0.46879099, 0.49095688, 0.51312277, 0.53528865,
        0.55745454]),
 <BarContainer object of 10 artists>)
```




```
[643]: #RACDIF1
       plt.figure(dpi=300)
       plt.hist(trace['beta'][:, 7], ec='w', alpha=0.9)
```

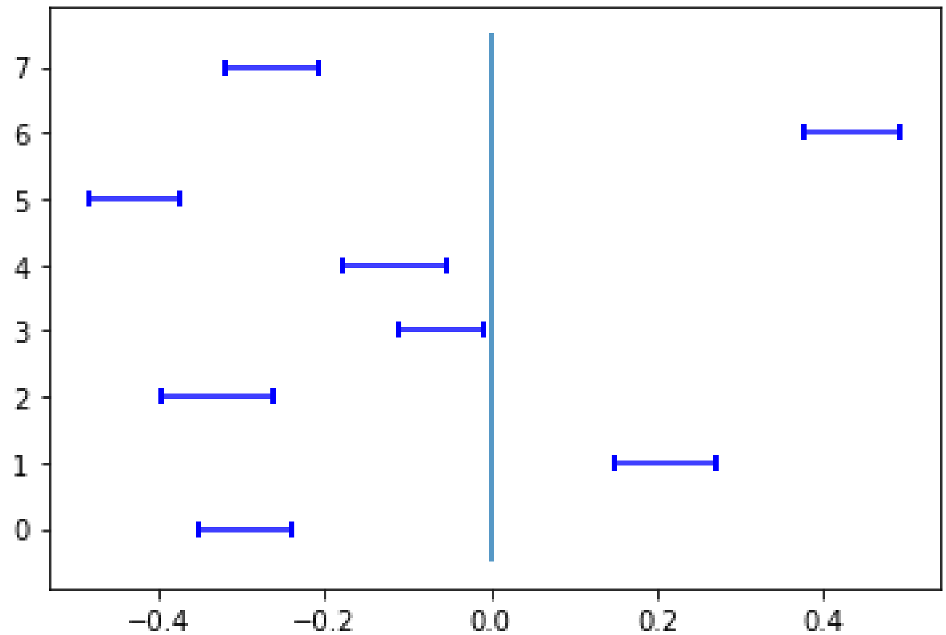
```
[643]: (array([  9.,  51., 171., 406., 543., 459., 251.,  86.,  21.,   3.]),
        array([-0.35909741, -0.33899009, -0.31888278, -0.29877547, -0.27866816,
               -0.25856084, -0.23845353, -0.21834622, -0.1982389 , -0.17813159,
               -0.15802428]),
        <BarContainer object of 10 artists>)
```



[644]:
```
"""#DISCAFF
plt.hist(trace['beta'][:, 8])"""
```

[644]: "#DISCAFF\nplt.hist(trace['beta'][:, 8])"

[671]:
```
plt.vlines(0, -0.5, 7.5)
for i in np.arange(8):
    posterior = trace['beta'][:, i]
    pts = [np.percentile(posterior, 2.5), np.percentile(posterior, 97.5)]
    plt.hlines(i, pts[0], pts[1], color='b')
    plt.scatter(pts, [i, i], color='b', lw=2, marker='|')
```



[781]:
```
[trace['beta'][:, i] for i in np.arange(8)]
labels = ['Environment', "Nat'l Security", 'Welfare', 'Social Security', 'Gun␣
↪Regulation', 'Abortion', 'Homosexuality', 'Race Discrimination']
idea = pd.DataFrame(columns=['x', 'label'])
i = 0
while i < len(labels):
    df = pd.DataFrame(trace['beta'][:, i].flatten()).rename({0:'x'}, axis=1)
    df['label'] = labels[i]
    idea = idea.append(df)
    i += 1
idea['hue'] = idea['x'] < 0
idea = idea.sort_values('x', ascending=False)
idea
```

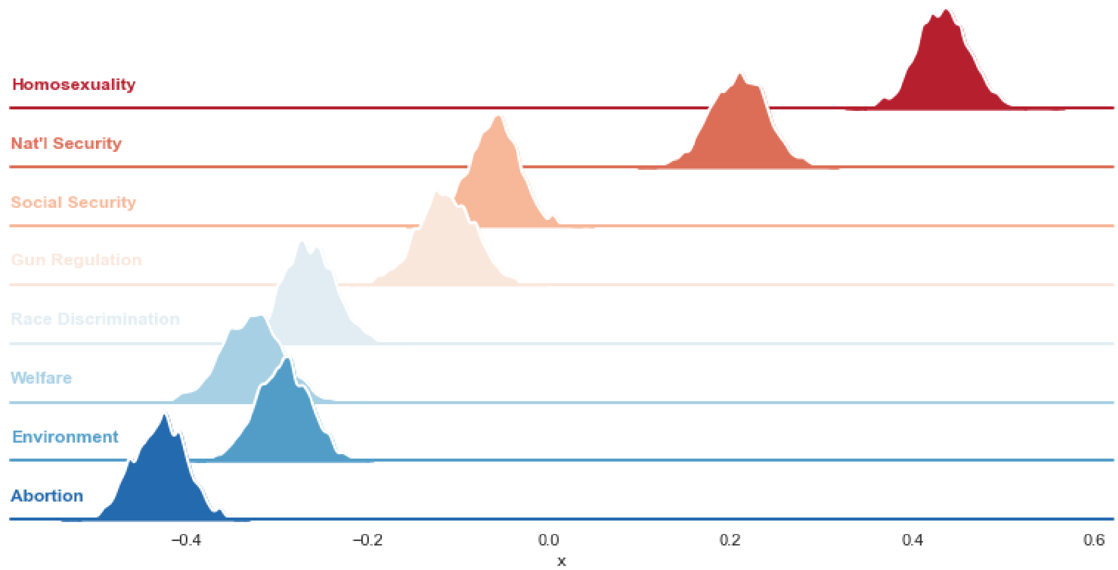
[781]:

	x	label	hue
286	0.557455	Homosexuality	False
432	0.521324	Homosexuality	False
580	0.520051	Homosexuality	False
771	0.519373	Homosexuality	False
485	0.516107	Homosexuality	False
…	…	…	…
451	-0.506627	Abortion	True
1630	-0.509734	Abortion	True
1612	-0.510869	Abortion	True
151	-0.514576	Abortion	True
778	-0.529190	Abortion	True

```
[16000 rows x 3 columns]
```

[787]:
```
import seaborn as sns
sns.set_theme(style="white", rc={"axes.facecolor": (0, 0, 0, 0)})

plt.figure(dpi=300)
# Initialize the FacetGrid object
pal = sns.cubehelix_palette(10, rot=-.25, light=.7)
g = sns.FacetGrid(idea, row="label", hue="label", aspect=15, height=.75,␣
↪palette='RdBu')

# Draw the densities in a few steps
g.map(sns.kdeplot, 'x',
      bw_adjust=.5, clip_on=False,
      fill=True, alpha=1, linewidth=1.5)
g.map(sns.kdeplot, 'x', clip_on=False, color="w", lw=2, bw_adjust=.5)

# passing color=None to refline() uses the hue mapping
g.refline(y=0, linewidth=2, linestyle="-", color=None, clip_on=False)


# Define and use a simple function to label the plot in axes coordinates
def label(x, color, label):
    ax = plt.gca()
    ax.text(0, .2, label, fontweight="bold", color=color,
            ha="left", va="center", transform=ax.transAxes)


g.map(label, 'x')

# Set the subplots to overlap
g.figure.subplots_adjust(hspace=-.5)

# Remove axes details that don't play well with overlap
g.set_titles("")
g.set(yticks=[], ylabel="")
g.despine(bottom=True, left=True);
#plt.savefig("/Users/alanjian/Desktop/Data 102/Beta Posteriors")
```

```
<Figure size 1800x1200 with 0 Axes>
```


Homosexuality
Nat'l Security
Social Security
Gun Regulation
Race Discrimination
Welfare
Environment
Abortion
−0.4
−0.2
0.0
0.2
0.4
0.6
x

[ ]: