DATA 102: Data, Inference, and Decisions
University of California, Berkeley
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Final Project Written Report

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Our final project explores the concepts of Multiple Hypothesis Testing and Bayesian Hierarchical Modeling using the Five Thirty Eight data on 2018 U.S. primary elections.

Data

The datasets we used in our project are split into Republican and Democrat candidates for the 2018 U.S. primary. They contain information about the candidates (like their role and district) and endorsements from various political groups and influential people. This data was gathered from various sources by Five Thirty Eight including Ballotpedia, VoteSmart, and candidate websites. Each row in the data represents one candidate, also showing the percentage of votes each candidate got in the primary and whether they won or not.

However, the data doesn't include details about the voters. So, high percentages for a candidate might mean they got a lot of votes, or it could mean they got most of the votes from a small number of people. In that way, the assumptions we are making that all wins are equal may not be fully representative.

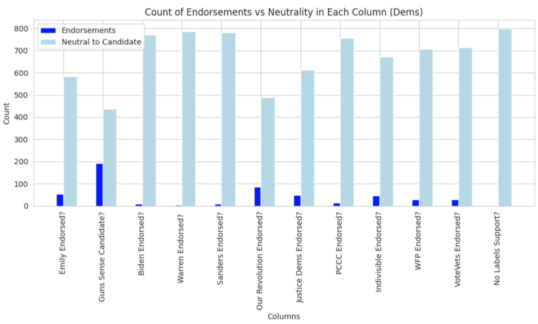
Moreover, while the data had details on the Democratic candidates (i.e. if they had previously held office, LGBTQ-identifying, etc.), that information was not available for Republicans. We believed that this could have also helped us in seeing if that could influence a candidate's inclusiveness for RQ II. Additionally, there are more Democratic candidates than Republican (811 vs 775), so the analyses in RQ II focus purely on Democratic candidates as they make up a larger chunk of the data, meaning all results apply to their party alone.

Even though we had a good amount of endorsements from different causes, we wished we had access to all endorsements from specific groups throughout the campaign. This lack of comprehensive endorsement information limits our analysis on confidently answering if endorsements has an effect on voting behavior at large. To clarify the data on endorsements, endorsements are labeled as "Yes" if a candidate got an endorsement, blank if the group was neutral, and "No" if the group actively opposed the candidate.

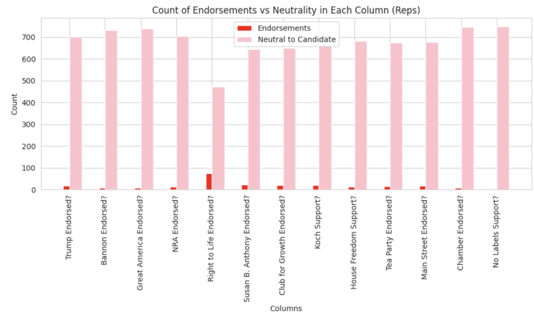
EDA

Research Question I

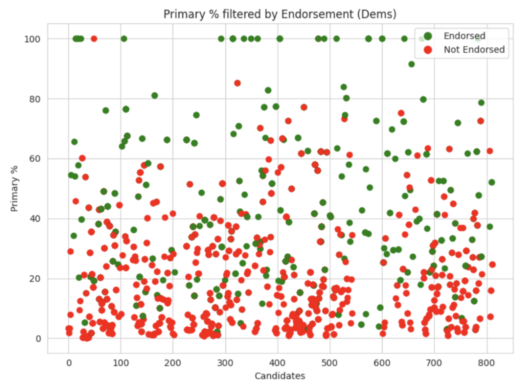
(See Figure 1) The qualitative visualizations (shown in first row) show that that for both Republicans and Democrats, there were very few endorsements by each cause-specific group/notable figure in the party. This prompted us to wonder whether the existence of a rare endorsement for these groups had some sort of influence on election outcome, motivating our RQ I. The quantitative visualizations (shown in second row) gave us indications that there seems to be a larger share of primary % for candidates who were endorsed rather than those who were not endorsed in any capacity. We can confirm this with aggregate hypothesis tests on the presence of endorsements, or multiple hypothesis testing, to further investigate this claim; again, another motivating factor for RQ I.



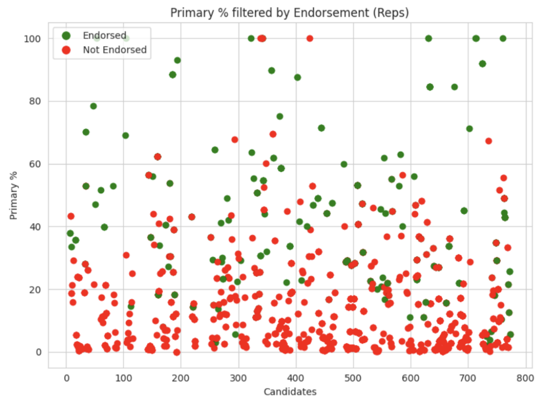
(a) [D] Counts of Endorsements vs Neutrality



(b) [R] Counts of Endorsements vs Neutrality



(c) [D] Primary % by Presence of Endorsement



(d) [R] Primary % by Presence of Endorsement

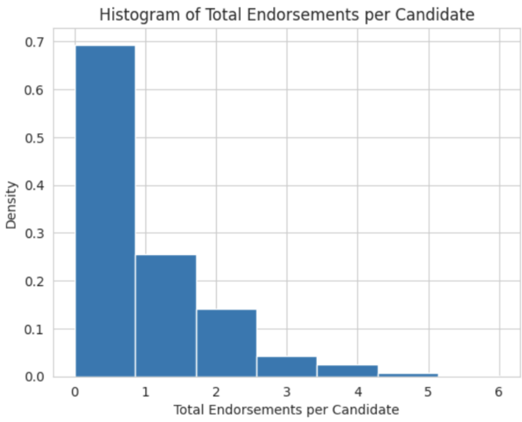
Figure 1: EDA for RQ I

Research Question II

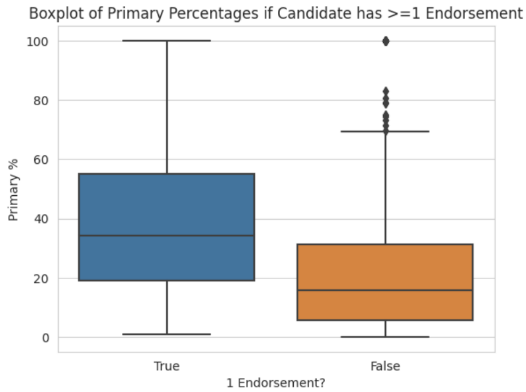
(See Figure 2) From the first visualization, we found that most candidates received 0 endorsements, with a concave decreasing trend as endorsements increase. The total possible endorsements is 13, and the maximum seen above is only above 5. We want to fit this quantitative variable to a distribution, and we think it's likely to be Binomial or Poisson from the above graph. We settle on the former later on in the report, but choosing the right distribution helps our Bayesian Hierarchical Model better reflect reality.

From the second visualization, we can tell that getting at least one endorsement increases the share of votes that a candidate can achieve, since the boxplot for having >=1 endorsement has a higher 50th percentile than the other.

This motivates our research question – total endorsements is an important determiner of a candidate's funds, political support and eventual success. We posit that it might depend on a candidate's ideological inclusiveness, such that this Bayesian Hierarchical Model can help us build.



(a) Total Up Endorsements per Candidate



(b) Primary % if Candidate has 1 Endorsement

Figure 2: EDA for RQ II

1 Research Question I (Multiple Hypothesis Testing)

Did endorsements from groups supporting specific causes affect the chance of winning in the 2018 primary?

1.1 Hypotheses

**Note that when we mention "not endorsed" here, we mean that the group is neutral to the candidate - neither endorses nor anti-endorses.*
We came up with 7 hypothesis tests:

1. Democratic candidates with endorsements from Emily's List have a higher probability of winning than those not endorsed.
2. Democratic candidates with endorsements from WFP have a higher probability of winning than those not endorsed.
3. Democratic candidates with endorsements from Guns Sense have a higher probability of winning than those not endorsed.
4. Democratic candidates with endorsements from VoteVets have a higher probability of winning than those not endorsed.

5. Republican candidates with endorsements from Right to Life have a higher probability of winning than those not endorsed.

6. Republican candidates with endorsements from NRA have a higher probability of winning than those not endorsed.

7. Republican candidates with endorsements from Club for Growth have a higher probability of winning than those not endorsed.

It makes sense to test many hypotheses instead of just one in order to answer our question as we are able to explore the overall question more comprehensively by looking at the effect of endorsements from specific groups, within each party. This in turn makes it more likely for us to highlight actual correlations between group endorsements and a candidate's likelihood of winning as opposed to attributing it to random chance. Since the number of endorsements each group gives out is also unique, by testing for individuals hypotheses, we do not run the risk of generalizing trends when trying to prove our overall question.

1.2 Methods

For each hypothesis, we are testing for the correlation between endorsement received from a particular group and the likelihood of endorsed candidates winning the primary. We do this by the overall difference in means for the number of endorsed candidates that win vs the number of neutral (neither endorsed nor anti-endorsed by group) that win.

For instance, in the first hypothesis, we take the average number of democratic candidate wins out of those endorsed by the group Emily's List and subtract the average number of democratic candidate wins out of those that were neutral by Emily's List.

The reason for choosing to analyze correlation is so that we are able to analyze the effect of endorsements by specific groups affecting the likelihood of candidate wins within each party. By using the difference in means as our test statistic for each hypothesis test, we are also able to see the effect of specific group endorsements on the overall win rate very clearly. If the difference is positive and close to 1, we can conclude that there is a very strong positive correlation between that group's endorsement and the overall likelihood of candidates winning within that party. Conversely, if the difference is negative and close to -1, we can conclude that there is a very strong negative correlation between that group's endorsement and the overall likelihood of candidates winning within that party. Lastly, if the difference is close to 0, we have to conclude that there is not a very strong correlation between receiving endorsements from that particular group on the overall likelihood that candidates win the primary.

We are correcting for multiple hypothesis tests using Bonferroni correction and the Benjamini-Yekutieli (BY) procedures.

The Bonferroni method controls for family-wise error rate (FWER) by guaranteeing that the FWER is less than or equal to alpha (which we set as 0.05 in this case) for our 7 tests. This uses a p value threshold of alpha/7. This is more conservative than the BY method as we are ensuring that for each one of the tests, the probability of a false positive is no greater than 0.05/7 (=0.00714) and we usually make fewer discoveries to avoid risking any false positives.

Conversely, the BY method is an extension of the Benjamini-Hochberg (BH) procedure but it accounts for dependence between each of the 7 tests that we have chosen to answer our overarching question. The BY procedure accounts for scenarios where the tests might be dependent and allows for a wider range of correlation structures among the tests. The main distinction in the BY procedure lies in the calculation of critical values to control the FDR. We use it to control False Discovery Rate (FDR) in multiple hypothesis testing scenarios and BY guarantees that the FDR is less than or equal to alpha (0.05) for the 7 tests. This is a less conservative test than Bonferroni as the FDR allows for 0.05 of the discoveries to be wrong on average, leading to a higher expected proportion of false positives among the identified significant results.

1.3 Assumptions

In our multiple hypothesis testing framework, we assume the following:

1. The dataset's single-issue endorsement groups are a comprehensive and accurate representation of all single-issue endorsement groups involved in supporting candidates during the 2018 U.S. primary.

2. The effects of endorsements from distinct issue groups on the likelihood of winning are consistent and uniform.

3. Endorsements originating from different groups may exhibit some level of interdependence or correlation (as politics is a complicated field where endorsements from significant groups/figures may have some effect on one another).

4. The impact of group endorsements on the likelihood of Democratic and Republican candidates winning is the same.

1.4 Results

The p-values that we got in correspondence with the hypotheses listed in the 'Hypotheses' section were: 0, 0.0464, 0.0046, 0.001, 0.0272, 0.0124, and 0.003. These correspond to significance decisions of True, False, True, True, False, True, True for BY correction (5 discoveries out of 7).

Meanwhile, controlling for FWER using Bonferroni, we made 4 discoveries out of our 7 tests. We believe that BY (controlling for FDR) is more appropriate for our research question as we are trying to estimate the overall effect of group endorsements on the likelihood of winning the 2018 primary elections. Since Bonferroni correction is very conservative, while we have a reduced chance of any false positives, we are also increasing the chance of getting false negatives as a result. To clarify, FWER is defined as the probability that any of the hypothesis tests (in this case, 1 of the 7) is a false positive. Meanwhile, FDR is defined as the average of the reality being untrue when our test predicts to be true (i.e. $P(R = 0|D = 1)$), over all of our tests.

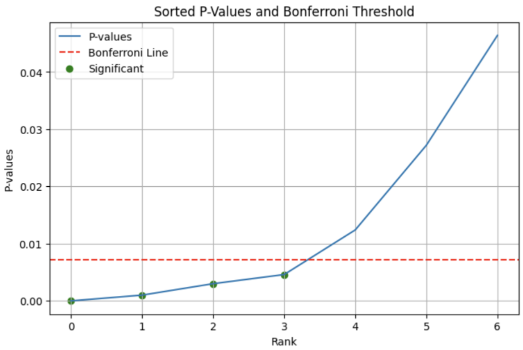


Figure 3: Bonferroni Correction (4 discoveries)

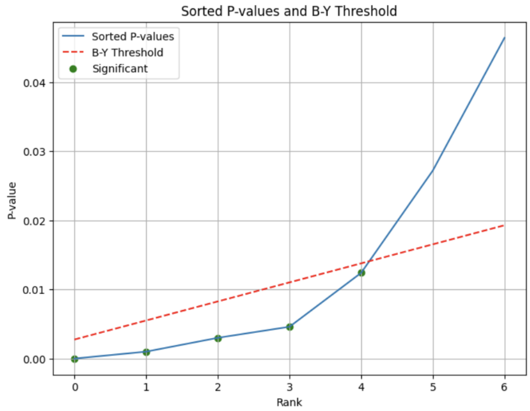


Figure 4: BY Correction (5 discoveries

In our context, getting false negatives are not less detrimental to our model than false positives so increasing the likelihood of false negatives is something we want to avoid as well. This affects our ability to accurately generalize the effect of group endorsements on the likelihood of winning. On the other hand, the BY procedure is less stringent and allows us to better balance between controlling false discoveries and being more sensitive in detecting true effects.

The two correction methods we chose to use were Bonferroni and BY correction. We opted for the implementation of the BY correction over the BH method due to the former's consideration for hypotheses independence, in contrast to the assumption of dependence in the latter, recognizing that we cannot assume independence for a subject as complex as political endorsements. The equation for calculating significant p-values through BY is $P_{(k)} \leq \frac{k}{m \cdot c(m)}\alpha$ where m = the total amount of tests and k = rank of the p-value when all p-values are sorted. Our comparative analysis between the two corrections revealed that BH projected 7 discoveries, contrary to the 5 predicted by BY, reaffirming our belief that the independence of hypotheses might not hold true in our context.

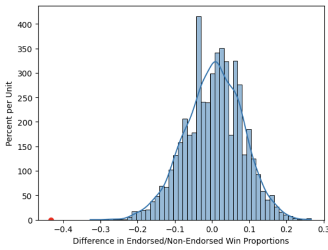
1.5 Discussion

1.5.1 Reflection on Methods

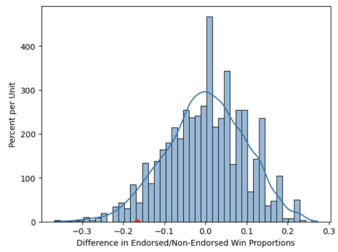
After applying our correction procedures, all discoveries except two (test #2, which tested Democrat candidates being endorsed by WFP vs those who were not on the proportion of candidate win, and test #5, which tested Republican candidates being endorsed by Right to Life vs those who were not) remained significant. We believe that such a large proportion remained significant because the existence of an endorsement raises political visibility for a candidate and therefore, greatly influences their chances of winning. This is particularly true within the U.S. as many voters now are single-issue voters and are thus easily swayed into voting for a candidate based on their stance/approval for a certain issue. Since we chose cause-specific groups for our hypotheses test we predicted this may have been the case.

1.5.2 Decisions

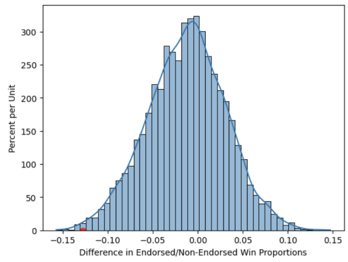
We reject the null hypothesis for all tests except for tests 2 and 5, which we failed to reject after applying Benjamini-Yekutieli correction.



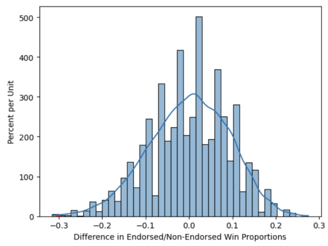
[D] Emily's List Endorsement: p=0.0



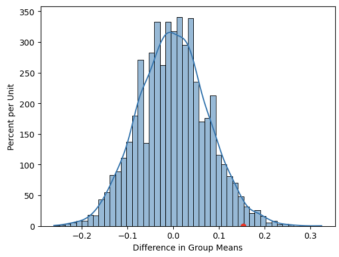
[D] WFP Endorsement: p=0.0464



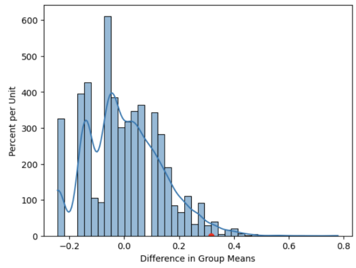
[D] Guns Sense Endorsement: p=0.0046



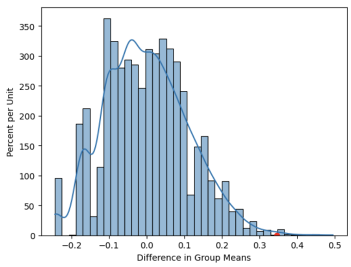
[D] VoteVets Endorsement: p=0.001



[R] Right to Life Endorsement: p=0.0272



[R] NRA Endorsement: p=0.0124



[R] Club for Growth Endorsement: p=0.003

1. We reject the null hypothesis that there is no difference in the proportion of winning for a Democratic candidate endorsed by Emily's List and a Democratic candidate who Emily's List is neutral to.

2. We fail to reject the null hypothesis that there is no difference in the proportion of winning for a Democratic candidate endorsed by WFP and a Democratic candidate who WFP is neutral to.

3. We reject the null hypothesis that there is no difference in the proportion of winning for a Democratic candidate endorsed by Guns Sense and a Democratic candidate who Guns Sense is neutral to.

4. We reject the null hypothesis that there is no difference in the proportion of winning for a Democratic candidate endorsed by VoteVets and a Democratic candidate who VoteVets is neutral to.

5. We fail to reject the null hypothesis that there is no difference in the proportion of winning for a Republican candidate endorsed by Right to Life and a Republican candidate who Right to Life is neutral to.

6. We reject the null hypothesis that there is no difference in the proportion of winning for a Republican candidate endorsed by NRA and a Republican candidate who NRA is neutral to.

7. We reject the null hypothesis that there is no difference in the proportion of winning for a Republican candidate endorsed by Club for Growth and a Republican candidate who Club for Growth is neutral to.

From the aggregate results, we believe that we can assume that endorsements from cause-specific groups affect the chances of winning the primary, as a majority (5/7, or 71.43% of) p-values proved to be significant even after correction.

1.5.3 Limitations

First, as we only had access in our dataset to a number of specific groups' endorsements, we were only able to test the effect of these endorsements. Second, we were unsure if the hypotheses we had (groups we were testing) were dependent, so we had to rely on the more lenient test of BY rather than BH in order to control FDR.

To avoid p-hacking, we made sure to set our baseline p-value, or alpha, to be 0.05 beforehand and did not adjust our problem setup upon seeing our test results.

1.5.4 Additional Tests

If we had more data, we would want to first and foremost conduct hypothesis tests on other cause-specific groups' endorsements for the 2018 candidates. We could also group cause specific groups' endorsements into categories and then test these groups' endorsements as a whole if we had the data for multiple groups supporting 1 cause and their endorsements.

2 Research Question II (Bayesian Hierarchical Modeling)

Can we fit a Bayesian mixture model to describe the ideological inclusiveness of a candidate's campaign platform based on the number of endorsements they received in the 2018 Democratic primaries?

(Note: only evaluating this hierachical model on Democratic candidates.)

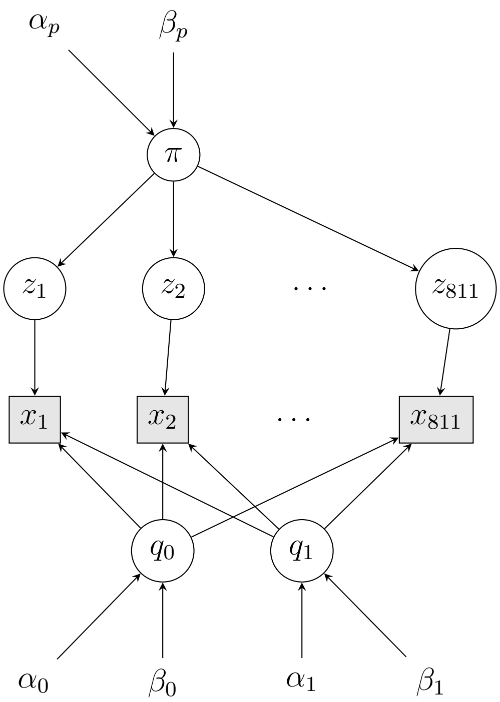
Definition of "inclusiveness"
We use the term "inclusiveness" to refer to how expansive and diverse a candidate's campaign platform is, in terms of including the views of different interest groups. For example,

a candidate from the Green Party running solely on environmentalism and climate justice at the expense of other issues like abortion, gun rights, the economy, etc. would not be "inclusive."

Hypothesis
The more inclusive a candidate's platform, the more total endorsements they will receive.

2.1 Methods

2.1.1 Graphical Model



This issue aligns with the application of a Bayesian mixture model, designed for the identification of clusters within a dataset. It leverages our predetermined assumptions and the observed variable, namely the quantity of endorsements, to determine the distribution of unobservable parameters. These parameters encompass the inclusivity of a candidate and the likelihood of receiving endorsements. See more details in 2.1.3.

2.1.2 Variables

Observed Variables

- x_1, ... x_{811}: count of endorsements per Democratic candidate, found by totalling up columns of "Yes" for endorsement columns in raw data

Hidden Variables

- π: probability that a single candidate is inclusive
- z_1, ..., z_{811}: per candidate, 1 if candidate runs on an inclusive campaign platform, 0 if candidate did not

- q_0, q_1: probability of being endorsed by an organization if endorsed and if not; a continuous random variable, bounded (0,1)
  (Note: We assume that there are two possible distributions determining the probability of being endorsed once for a given candidate, depending on whether their campaign platform is inclusive of different interests or not)

2.1.3 Categorizations in the Dataset

We are using the mixture model to identify groups in the dataset: Democratic candidates that ran on an inclusive campaign platform, and candidates that did not.

Under our hypothesis, there is a relationship between the inclusiveness of a candidate's platform to the likelihood of gaining one endorsement and thus the number of endorsements they would receive.

If a candidate is running on a platform welcoming of diverse interests, then the probability they get any one endorsement is higher, and more interest groups would be likely to sponsor and endorse the candidate. E.g. Brent Welder ran in U.S. House Kansas District 3, with endorsements from Gun Sense, Sanders, Our Revolution, Justice Dems and the Progressive Change Campaign Committee. Welder likely ran on a platform including gun law reformation, the Green New Deal, universal healthcare and more.

If a candidate is running on a narrow platform, the probability of getting any one endorsement is lower and less total count of interest groups would endorse them.

2.1.4 Justifications of Distributions

- Probability Inclusive: Beta
  A probability bounded (0, 1) that a candidate is inclusive. With no information, we use a Beta(1,1) prior. We chose a Beta(1,1) over a Uniform(0,1) distribution to allow the flexibility of changing the distribution later, since the shape of a Beta can be changed by varying alpha and beta parameters.

- Inclusiveness: Bernoulli
  A candidate ran on an inclusive platform with Inclusiveness=1, and not otherwise, with probability equal to the result of the Beta distribution above. We assume that there can be a clear distinction between candidate able to balance many interests versus those not able to.

- Probability of One Endorsement: Beta
  A probability should be bounded (0, 1), which Beta distributions are. They are also especially appropriate since they afford the random variable a great deal of flexibility in terms of shape. The 2 distributions depending on the inclusiveness of a given candidate's platform (Bernoulli, so either 0 or 1) can be skewed differently.

  - Parameters of One Endorsement: Beta
    We begin with two Beta(1,1) distributions for both candidates who are inclusive and not. We hold back from making any decision on how different the probabilities of a candidate getting an endorsed might differ between these groups.

This means we know nothing about the relationship between getting endorsed by a single endorsing organization and the inclusiveness of a candidate's platform – we do not know if q0 (not inclusive; when z = 0) is larger than q1 (inclusive; when z = 1). We will derive a conclusion about this relationship by plotting the posterior distributions of q0 and q1.

- Number of Endorsements: Binomial
  Endorsements should be modelled as counts and the minimum number of endorsements is 0 and maximum 13. Here, success would mean a candidate getting endorsed by an interest group out of the 13 groups in the dataset. p: the probability of a candidate getting a single endorsement, modelled by q, the Beta.

  We chose a Binomial over a Poisson distribution because the latter is best applied when N is large and p is small. While p is small in this case, as most candidates got 0 out of 13 endorsements and no one got over 6, N is not large.

2.2 Assumptions

In the above model, we assume the following:

1. Inclusiveness can be reduced to a binary variable of inclusive or not inclusive, when a candidate's stance on different issues can be multifaceted and nuanced. This is definitely the largest assumption of our study, as inclusiveness might in fact be a continuous variable, perhaps a Beta distribution between 0 and 1.
2. There is one meaning to inclusiveness: the diversity and expansiveness of a candidate's platform. It could instead be how 'muddled' a candidate is about their platform, impeding them from getting endorsed by specific groups.
3. A Binomial distribution for the number of endorsements: Whether an endorser supports a certain candidate is independent of another endorser. This could be untrue, as Sanders' support for a candidate could determine if Our Revolution supports them since the organization is heavily influenced by him. Similarly, the PCCC was spun out of Elizabeth Warren's campaign, so there could be a similar relationship there.
4. Endorsing organizations decide to sponsor a candidate solely because of their platform or individual characteristics. The specific district they are running in could instead impact that decision: the partisan lean of the district, the strength of the endorsing group's grassroots organizing in the district, whether the district has historically voted in favor of their policy fights, etc.

2.3 Results

2.3.1 Summary of Results

After we fit our model, we graphed our Bayesian mixture model's density based on its mean inclusiveness posterior and its mean posterior on being endorsed once. The data below is in blue while the red line indicates our model's density.

PyMC

```python
N = len(y_obs)
max_endorsements = len(dems_endorsements)
alphas = [1, 1]
betas = [1, 1]

with pm.Model() as model:
    pi = pm.Beta("probInclusive", alpha = 1, beta = 1) #Hidden variable

    z = pm.Bernoulli('inclusiveness', p = pi, shape = N #Hidden variable
    )

    q = pm.Beta('probEndorsedOnce', alpha = alphas, beta = betas, shape = 2) #Hidden variable

    X = pm.Binomial(
        'numEndorsements', n = max_endorsements, p = q[z], observed=y_obs #Observed variable
    )
    trace = pm.sample(500, chains = 2, return_inferencedata = False)
```

```
100.00% [1500/1500 02:49<00:00 Sampling chain 0, 0 divergences]
100.00% [1500/1500 02:15<00:00 Sampling chain 1, 0 divergences]
```

Figure 6: PyMC Model for RQ II

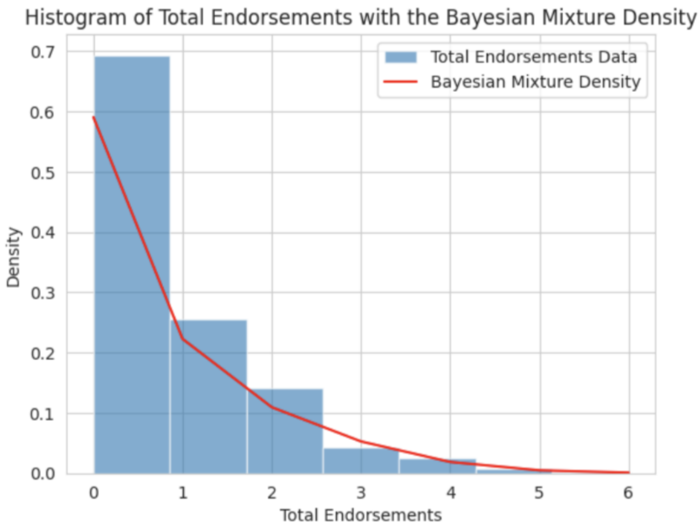


Figure 7: PyMC Results with Original Data

The model fits our observed values – Total Endorsements – fairly well. This is in comparison to other models we tested, as detailed in the Discussion section. This implies that our assumptions of flat priors - or, Beta(1,1) densities - for the hidden variables was fair and generally flexible for the endorsements to inform the actual densities. Also, the way we fed the variables into the endorsements is validated by the generally decent fit of our mixture model.

2.3.2 Quantifying Uncertainty

Probability of Inclusiveness of a Candidate

We quantified uncertainty by finding the 95% credible interval for the posterior distribution of the probability of a candidate being inclusive (π).

There is a 95% probability that the true probability of a single candidate being inclusive is between 0.540 and 0.756. Since this is greater than 0.5, there are more candidates that are inclusive. A political candidate would want to be more ideologically inclusive of the ideas of different interest groups, both to appeal to a larger voting population as well as more endorsing organizations offering funding support.

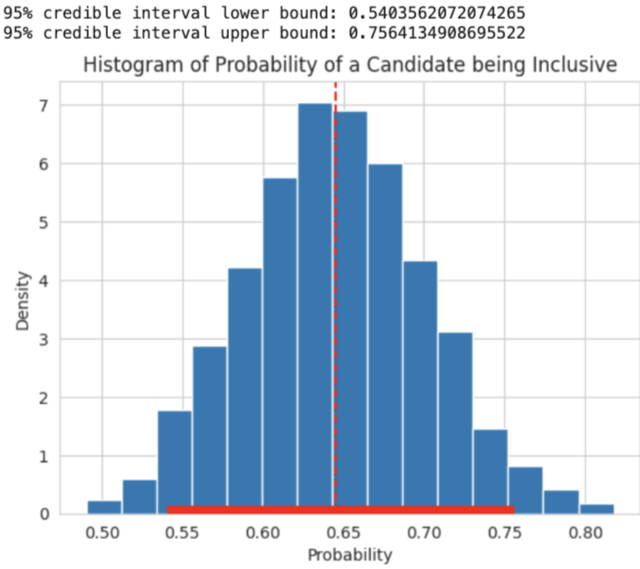


Figure 8: Histogram for π trace samples

Probability of a Candidate getting 1 Endorsement

We quantified uncertainty by finding the 95% credible interval for the posterior distribution of the probability of a candidate getting 1 Endorsement (q).
Earlier in the Methods section, we assumed that q comes from 2 distributions, determined by whether they are inclusive or not (z = 0 or 1). We thus make 2 histograms, one for q0 (Figure 6) and q1 (Figure 7).

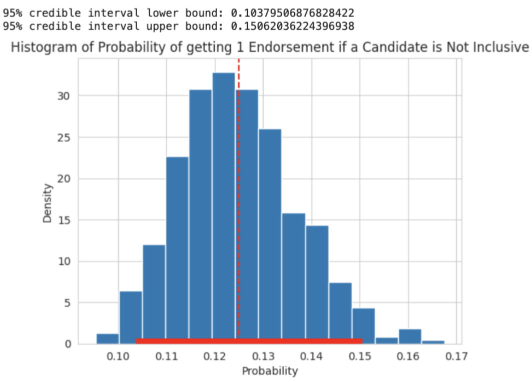


Figure 9: Histogram for q0 trace samples

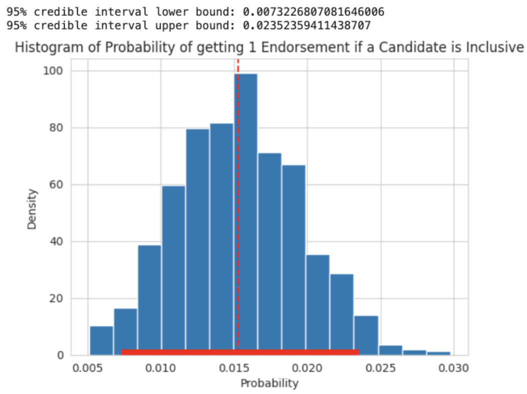


Figure 10: Histogram for q1 trace samples

There is a 95% probability that the true probability of a candidate getting 1 endorsement is between 0.104 and 0.151.
There is a 95% probability that the true probability of a candidate getting 1 endorsement is between 0.007 and 0.024.
Given that the credible intervals for candidates who are inclusive and not inclusive getting 1 endorsement do not overlap at all, we can be very certain that candidates who are not inclusive are more likely to be endorsed by any one endorsing organization.
This casts doubt on our hypothesis that candidates who are more inclusive get more total endorsements. To further confirm this, we investigate total endorsements achieved by

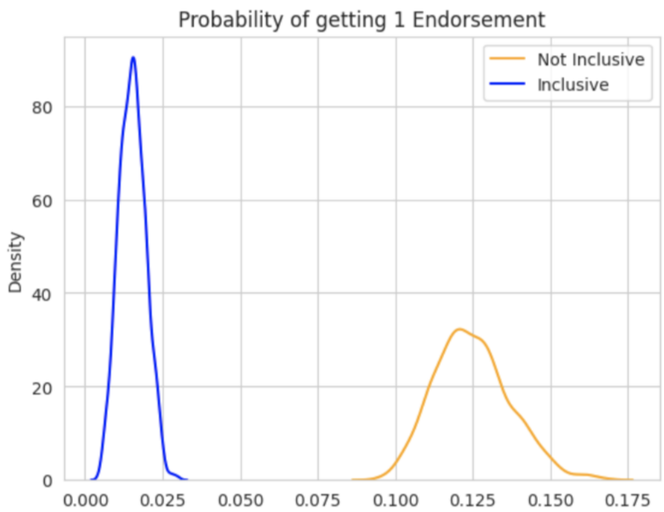
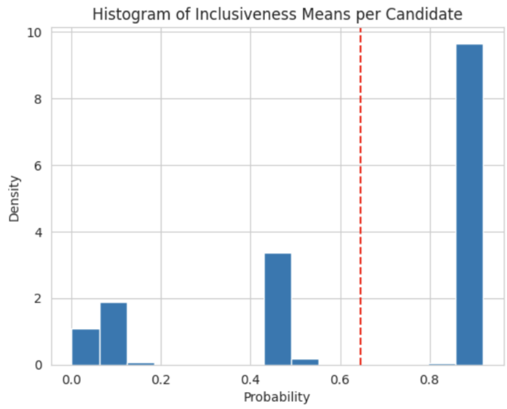


Figure 11: KDE plot for both samples

candidates who are inclusive or not inclusive.



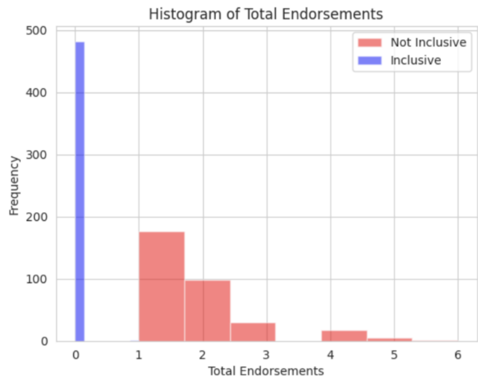


Figure 12: Inclusiveness categorizations, and total endorsements given classifications

Based on our posteriors, it is almost certain that a candidate that did not run on an inclusive platform is more likely to get more total endorsements, and at the very least 1. Candidates who ran on an inclusive platform are more likely to get 0 endorsements.

2.3.3 Findings

This makes us conclude that our initial hypothesis was wrong, and in fact it was the opposite relationship: Inclusive candidates get less total endorsements.

While this goes against the intuition we presented at the beginning of this paper – that inclusive candidates would be more welcoming of different ideas and thus may be more likely to get any one endorsement – it's possible that we made a mistake in framing "inclusiveness" as a variable.

Perhaps candidates who are "inclusive" have muddled stances, too split between different ideas or not clearly articulating the platform and its constituent policies that they are advocating for. As such, it is difficult to get endorsements because the more "inclusive" a candidate presents themselves, the less likely they seem to be a strong advocate for a particular interest group.

But what about candidates with many endorsements?

A possible answer is that in assuming a Binomial distribution for the total number of endorsements, we assumed that each "trial" (each endorsement) was independent of all others. In actuality, different endorsing organizations advocate for different interests and policies, which may overlap.

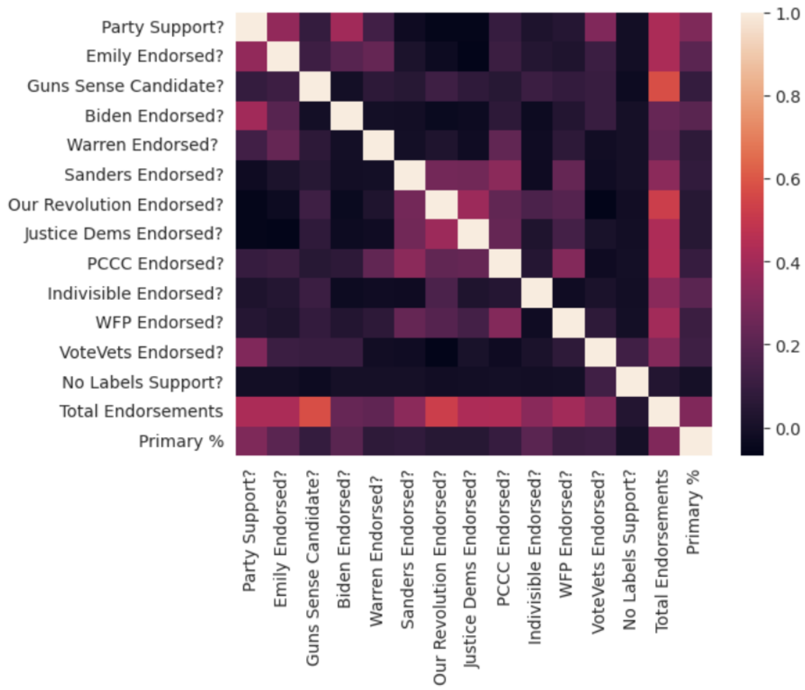


Figure 13: Correlation heatplot of all organizations endorsements

There is some correlation between a candidate being endorsed by some pairing of Bernie Sanders, Our Revolution, Justice Dems, the PCCC and WFP. Furthermore, of the 6 candidates with more than 4 total endorsements, 2 were endorsed by Sanders, Our Revolution, Justice Dems and the PCCC.

These 5 organizations do have overlapping policy fights. Justice Democrats, the Working Families Party (WFP), the Progressive Change Campaign Committee and Our Revolution are all organizations looking to boost progressive candidates. Their websites mention similar campaign issues: a wealth tax, cancelling student debt, bold solutions to climate change, racial justice, making housing more affordable, etc. Our Revolution was even spun out of Bernie Sanders' 2016 presidential campaign, continuing his platforms from then.

If a candidate is endorsed by one of these 5 organizations, they are more likely to be supported by the rest.

Thus, it is not that candidates with many endorsements are uniting many issues under one platform, but that their platforms revolve around a set of policy changes that are in the overlap. Perhaps they are the few that manage to clearly articulate their stances on issues without it being muddled, allowing endorsers to be able to trust that they will advocate for them.

2.4 Discussion

2.4.1 Limitations

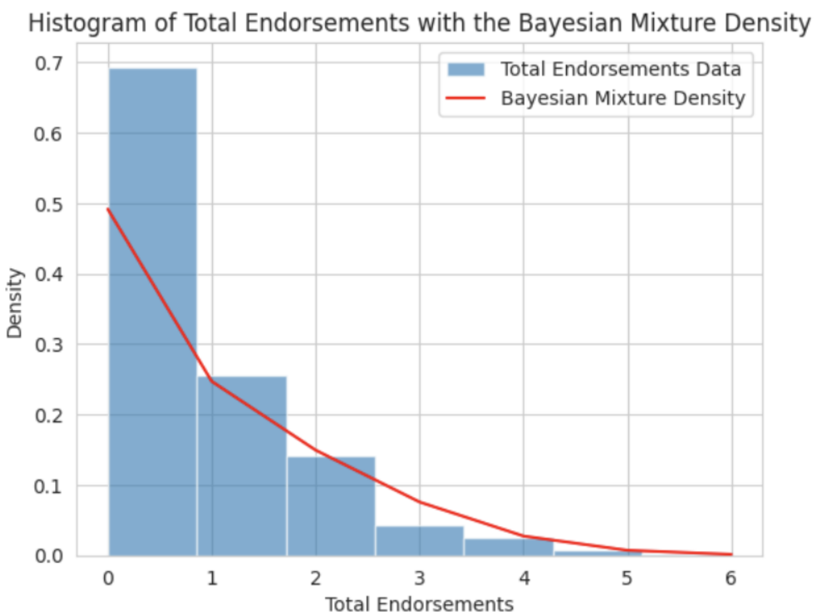
1. We fail to consider that inclusiveness could be a continuous variable, and reduce it to two simplistic groupings of inclusive or not inclusive

2. Those two groups map onto candidates with 0 or >=1 total endorsements (Fig 6). The model may thus not be very informative, and the groupings could map onto other qualities that aren't inclusiveness.

3. We only consider a "Yes" as an endorsement, and lump in a "No" and a neutral stance from an organization together. As a result, we fail to consider the difference between an organization actively working against a candidate or simply not commenting on them.

2.4.2 Other Models

We did try another model initially. The only difference was that we initially specified pi=0.5 instead of assigning it to be a Beta distribution.



Comparing the above histogram to the one plotted for the model with $\pi \sim$ Beta(1,1) , we can see that the histogram from the currently used model fits the actual total endorsements data better, especially in the first bin of the histogram with endorsements below 1.

Furthermore, since we're not sure what the actual probability of inclusiveness is, we felt it was better to make it a random variable by assigning it to a distribution, instead of fixing the model to our 0.5 assumption.

2.4.3 Additional Data

It would have been beneficial for the dataset to contain more columns representing possible endorsements from other important agencies or organizations, since this would have added more variance to our observed values, which is currently a discrete value from a small range of 0 to 6 due to the small number of possible endorsers we have to work with. This additional variance would have led us to be able to create a more meaningful classification between inclusive and non-inclusive candidates by giving us a more accurate and comprehensive number of total endorsements for each candidate.

3 Conclusion

With a rise of single-issue voting, candidates are faced with increased pressure to take strong stances on divisive political issues. From our study, an endorsement from a cause-specific group like Emily's List or the NRA would likely affect a candidate's chances of winning the primary. A candidate might thus want to maximize the number of endorsements they receive, but that is difficult: If they are ideologically inclusive of many different ideas, then their stances on them might be too muddled for an endorser to be sure that they would carry out policy changes for its policy fights.

From this, candidates in future primaries should attempt to maximize their endorsements from cause-specific groups, but must ensure that the policy fights in their platform are well-articulated and clearly delineated to both endorsers and voters.

These conclusions would be stronger with a longer list of endorsing organizations, and the allowance for inclusiveness to be a continuous variable. For future work, both our studies noted that there are multiple endorsers supporting similar causes (e.g. progressive issues). It would be interesting to group endorsers by policy fights, see if an endorsement from one organization in the group is correlated with "Yes" or "Neutral" from another in the group, and if that has correlation with likelihood of winning, primary percentage, etc.