The Role of Political Identity and Ideology in Affective Political Polarization

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Abstract—

Increasing political polarization in the United States has led to increased animosity and decreased cooperation between members of opposing parties as well as members of the public at large. The salience of this topic in modern discourse has led many researchers to attempt to measure political polarization. Recently, two distinct types of polarization have been defined - 'ideological polarization' or widening differences over matters of policy, and 'affective polarization,' feelings of animosity towards members of the opposing party regardless of belief. Affective polarization has been measured directly and indirectly in experimental settings, but never while subjects are experiencing actual political content. Here we use modern tools of facial, vocal, and physiological affect recognition in a multi-modal analysis of subjects watching politicians of both parties give speeches about both liberal and conservative topics.

Keywords— **Affective Computing, Political Polarization**

1. Introduction

Political polarization and associated issues have drawn increasing attention in public discourse throughout the world, but especially in the United States. Feelings of mistrust in the party one does not support have more than doubled since 1994, with supporters believing that the "opposing party's policies are so misguided that they threaten the nation's well-being"[1]

Political polarization can be subdivided into two different social effects: ideological polarization, or the tendency of the polity to hold divergent policy views, and affective polarization, the tendency of partisans to say that "the other party's members are hypocritical, selfish, and closed-minded, and they are unwilling to socialize across party lines, or even to partner with opponents in a variety of other activities."[2] Recent work suggests that affective polarization is the more salient concept when discussing polarization within US politics. Members of the US public tend to overestimate our ideological polarization[3], and recent campaigns for the US Presidency have even contained relatively little ideological content, instead relying on partisan cue to motivate voters[4].

The importance of this trend is difficult to overstate. A recent study claimed that only 13% of US voters would be willing to defect from a co-partisan candidate if that candidate were found to be violating democratic principles[5], indicating that partisanship is threatening to overwhelm deeply held values.

Existing methods of measuring affective polarization suffer from exposure to sampling bias, lack of generalizability, and inability to implement in real-world settings. We propose a system by which affective polarization can be measured directly while participants are experiencing real political content.

2. Background

A large body of literature has been produced studying affective polarization at societal scales. Some notable works include studies of the flow of campaign contributions from donors at the political extremes[6], the tendency for Tweets to only be retweeted within a partisan network[7], and the

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[1] *Political Polarization in the American Public, PEW Research Center, 2014*

[2] *The Origins and Consequences of Affective Polarization in the United States* Iyengar et al., Annual Review of Political Science 2019 22:1, 129-146

[3] *Does Media Coverage of Partisan Polarization Affect Political Attitudes?*, Matthew Levendusky & Neil Malhotra (2016) Political Communication, 33:2, 283-301

[4] *Does Party Trump Ideology? Disentangling Party and Ideology in America*, BARBER, M., & POPE, J. (2019). American Political Science Review, 113(1), 38-54.

[5] *Democracy in America? Partisanship, Polarization, and the Robustness of Support for Democracy in the United States,* Graham and Svolik, 2020

[6] *Ideological Donors, Contribution Limits, and the Polarization of American Legislatures*, Michael J. Barber, The Journal of Politics 2016 78:1, 296-310

[7] *Echo Chamber or Public Sphere? Predicting Political Orientation and Measuring Political Homophily in Twitter Using Big Data*, Colleoni et a., Journal of Communication, Volume 64, Issue 2, April 2014, Pages 317–332

partisan divergence of the "feeling thermometer" (described in section 2.1) in the American National Election Study[8].

A much smaller number of efforts have been made to measure the affective polarization of individual subjects. These efforts can be broken down into three categories:

2.1 Self-Report

Some authors simply ask subjects about their degree of animosity towards the other party, including questions such as the ANES 'feeling thermometer', which asks directly how "warm" or "cold" the subject feels to members of the same or opposing political party. Another example is asking the subject whether they would be unhappy having their child marry a member of the opposing political party[9].

However, self-report methods are subject to cognitive and social biases on the part of the subject (they may wish to appear less biased than they are) due to complicated interactions with the way partisanship is treated in US culture and media, as well as potential interactions with the assumed politics of the researcher.

2.2 Behavioral Measures

In this category fall various economic games where participants are informed of the party affiliation of their opponent. Highly partisan subjects are more likely to penalize members of the opposing party, including awarding less money in the Dictator Game and showing preference for less qualified co-partisans when awarding a college scholarship[10].

Another notable behavioral intervention involves measuring the effect of affective polarization on ideology. In one study, Republican participants are 25% more likely to support a liberal policy if they hear Donald Trump support it as compared to if they hear him oppose it[11].

Behavioral studies run properly have the benefit of avoiding most sources of cognitive bias. However, these results may be difficult to extrapolate into more general settings. We cannot know for sure to what degree the effect stems from the particulars of the experiment, and we have little insight into the affective experience of the participants.

2.3 Implicit Bias

Implicit Association Tests (IATs) have been widely used in the study of racial bias for twenty years. More recently IATs have been applied to other forms of bias, including partisan bias. The partisan bias effect size is nearly twice as large as the racial bias effect size[12].

Implicit bias tests are among the most neutral and defensible methods of measuring affective polarization because the cognitive component is minimized and the nature of the experiment is highly general. However, IATs still nominally require an experimental setting. Participants must opt-in and dedicate time to the endeavor while doing nothing else.

2.4 Prior Work

This work builds on the work of McDuff et al. (2013)[13], who were able to predict the candidate preferences of study participants based on their affective response to political speeches as measured by webcam video.

There have been two notable recent reviews of the literature discussing the differences between affective polarization and ideological polarization. Iyengar et al. (2019)[14] give more methodological context and background information while Finkel et al. (2020)[15] discuss this issue in an urgent moral and electoral context.

3. Proposed Work

In this study, we propose measuring multiple modalities of participant input as a means to measure and compare polarization as created by a sense of identification with a political leader, as well as polarization as created by a sense of identification with a political ideology. We define the following research question in this regard:

RQ1: In videos of politicians speaking, are people more emotionally responsive to the political alignment of the content they are hearing, or the political alignment of the politician who is speaking?

H1: We hypothesize that participants are more likely to be emotionally aligned to the ideological content in a political video rather than to the political

[8] *Political sectarianism in America* Finkel et al.SCIENCE 30 OCT 2020 : 533-536

[9] *A Social Identity Perspective on Polarization*, Iyengar et al. 2012

[10] *Fear and Loathing across Party Lines: New Evidence on Group Polarization,* Iyengar, S. and Westwood, S.J. (2015), American Journal of Political Science, 59: 690-707.

[11] *Does Party Trump Ideology? Disentangling Party and Ideology in America*, Barber & Pope, 2018

[12] *Fear and Loathing across Party Lines: New Evidence on Group Polarization*, Iyengar et al. 2014

[13] *Measuring Voter's Candidate Preference Based on Affective Responses to Election Debates,* McDuff et al.2013 Humaine Association Conference on Affective Computing and Intelligent Interaction

[14] *The Origins and Consequences of Affective Polarization in the United States* Iyengar et al., Annual Review of Political Science 2019 22:1, 129-146

[15] *Political sectarianism in America,* Finkel et al. 2020

alignment of the political figure presenting the content.

We propose a novel methodology that captures affect input in the form of webcam video and audio streams, as participants watch the political videos. Inspired by literature in affective polarization, we capture both implicit affective responses from the video and audio input, measured when participants are focussed on the video they are watching, but also explicit affective responses measured when we ask participants to react with their face, and with words to tell us how they feel.

4. Methodology

4.1 Participant recruitment

To ensure a participant base is eligible to vote in the United States and is equally represented among conservative and liberal demographics, we recruit participants from Prolific[16], who are between the ages of 18 and 100, were born in and reside in the United States (and therefore, qualify to vote), and have specified their political affiliation. We ran the study in two settings, once for Democrats who fit the above criteria and once for Republicans. The study protocol supports fully remote participation, enabling access to a geographically distributed population, even amidst global health concerns like COVID-19.

We collect data from 30 participants in total, 15 Republicans and 15 Democrats. We disqualified participants who reported misalignment between party, ideology, and voting behavior. In other words, we only accepted liberal Democrats who voted for Biden and conservative Republicans who voted for Trump. There were six such exclusions, leaving 24 participants in the study.

4.2 Multi-modal data collection

Affect classification has been shown to perform better when run on multi-modal datasets considered simultaneously.[17] We propose a method of multi-modal data collection and analysis in the form of video, audio, and survey questions and answers from participants. This study has been approved by MIT's Institutional Review Board (IRB). Participants on Prolific are pointed to a website we designed explicitly for the purposes of this study[18]. On the website, they are led through a consent form, which among other things seeks permission to record their webcam video and audio streams for the duration of the study. After these preliminary steps, participants' video and audio is captured continuously until they reach the study debrief section.

4.3 Study Design

Participants take an introductory survey that establishes a mood baseline for the experiment. They are given a walkthrough of good camera and lighting hygiene and have the opportunity to compare their own webcam stream with an example we provide for them. Then, they are shown a set of 4 political videos in a randomized order interspersed with palate cleansers which are also randomized from participant to participant as shown in Fig. 4.1. The political videos are particularly pertinent to our research question, because we have 2 videos with conservative content, one from Trump and one from Biden and 2 videos with liberal content, one each from Trump and Biden. This allows us to compare affective responses in a participant based on the subject's political alignment with the person speaking, Trump or Biden, i.e *identity* or political alignment with the content in the video, conservative and liberal, i.e *ideology.* So, we effectively record affective responses across four categories (D/D), (D/R), (R/D), (R/R), where D is Democrat, and R is Republican. The first occurrence denotes *identity* while the second occurrence denotes *ideology*. For example, (R/D) involves Republican identity and Democrat ideology. We retain this occurrence association for the rest of this paper.

Besides capturing participants' video and audio streams continuously for the course of the study to capture what we will henceforth refer to as **Implicit Affect (IA)**; we also ask participants to present explicit visual and aural responses to how each video "made them feel" at the end of each political video to ensure that an affective state is captured for each piece of media. From the vocal responses, we collect the **Explicit Textual Affect (ETA)** based on the content being spoken. In addition to the political videos, participants are also asked to explicitly react to the palate cleanser videos, to minimize anchoring bias.

4.4 Storage

We store the entire video and audio stream as one piece of data, identified by a 5 character alphanumeric code for each participant. In addition to this piece of affective data, we also capture self reported survey responses to the pre and post activity survey (See Appendix), timestamps that denote *when* a participant started watching a

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[16] https://www.prolific.co

[17] S. Siddharth, T. Jung and T. J. Sejnowski, "Utilizing Deep Learning Towards Multi-modal Bio-sensing and Vision-based Affective Computing," in *IEEE Transactions on Affective Computing*, doi: 10.1109/TAFFC.2019.2916015.

[18] https://www.affectingpolitics.com

political video and finished watching it, and the order in which the political videos were watched.

5. Analysis

We analyze the affective responses obtained from the above experiment using the following inputs

- Continuous facial affect detection
- Textual affect in vocal content from participants
- Remote photoplethysmography (rPPG) measurements via video input.

- Each **IA** segment is passed through the Affectiva Emotion SDK[19] to capture continuous measurements of the facial affect. The SDK reports measured values of the various emotions, joy, fear, disgust, sadness, anger, surprise, contempt. In addition to the emotions, it also provides us measures of engagement and valence. Engagement is calculated by the Affectiva SDK using the weighted sum of certain Facial action units (FAUs) from the Facial Action Coding System (FACS).[20] These are *Brow raise*, *Brow furrow, Nose wrinkle, Lip corner depressor, Chin raise, Lip pucker, Lip press, Mouth open, Lip suck,* and *Smile* (See figure 6.1). Valence is calculated by the Affectiva SDK as being *positive* when the *Smile* and *Cheek Raise* FAUs are observed and as being *negative* when the *Inner Brow Raise, Brow Furrow, Nose Wrinkle, Upper Lip Raise, Lip Corner Depressor, Chin Raise, Lip Press* and *Lip Suck* FAUs are observed.

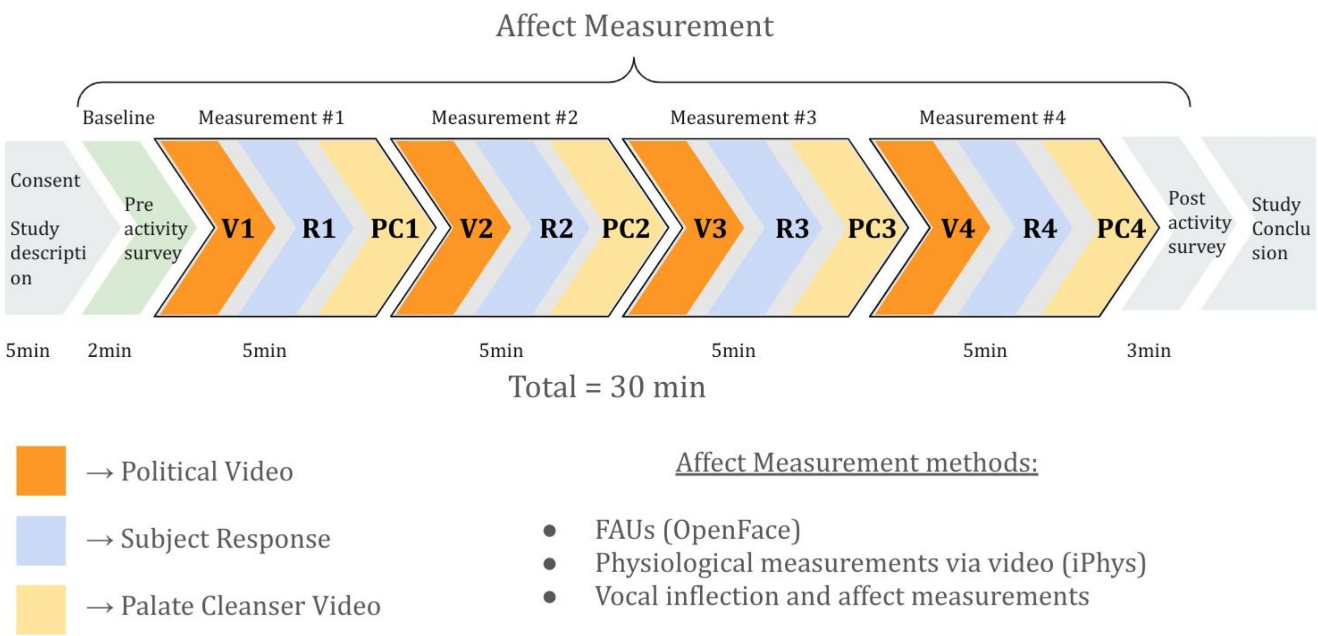


Fig 4.1 Study Design

We aggregate timestamps of video beginnings and endings per participant video into a CSV file along with the participant identifier code. We pass this CSV through our script. The script:

- Cuts up relevant segments of the video and audio, and collects
    - A ***baseline*** which is recorded as the user fixes their camera, and lighting
    - **IA, ETA** segments for each political video.

[19] Daniel McDuff, Abdelrahman Mahmoud, Mohammad Mavadati, May Amr, Jay Turcot, and Rana el Kaliouby. 2016. AFFDEX SDK: A Cross-Platform Real-Time Multi-Face Expression Recognition Toolkit. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (*CHI EA '16*). Association for Computing Machinery, New York, NY, USA, 3723–3726. DOI:https://doi.org/10.1145/2851581.2890247

[20] Ekman, P., Freisen, W. V., & Ancoli, S. (1980). Facial signs of emotional experience. *Journal of Personality and Social Psychology, 39*(6), 1125–1134

- Each **ETA** segment is passed through the TextBlob, a text sentiment analysis service from the Python natural Language Toolkit[21], to detect the polarity and subjectivity in the tone and the text of the message. Polarity is a measure that is similar to valence, and can be negative, neutral or positive, and ranges numerically from -1 to 1. Subjectivity is a measure of how subjective or objective a participant's opinion is, and ranges from 0 (objective) to 1 (subjective).
- Each **IA** segment is passed through an rPPG script in MATLAB that calculates the rPPG values and the heart bpm.

We analyze these various pieces of data, and compare them to our 4 categories defined earlier, (D/D), (D/R), (R/D), (R/R) along with the self reported political leaning of the participant, to measure the intensity and distribution of affective polarization.

<u>Modeling party affiliation as a predictor of affect</u>

We treat the interaction between political affiliation and test condition as independent variables, and each of the affect signals as a separate dependent variable. We retrieve the variable coefficients using multi-level linear regression, with each subject assumed to have a random intercept associated with their baseline affect.

<u>Modeling affect as a predictor of identity</u>

We build a logistic regression model to predict party affiliation, the dependent variable, in terms of the test condition and affect signals, the independent variables. The best subset of independent variables was selected using backwards stepwise selection, leaving just engagement, valence, and joy.

6. Results

We collected responses from 30 participants, equally distributed among Republicans and Democrats. However, after dropping ideological defectors like a Republican participant voting for Biden or vice-versa, we have 10 Republican participants and 14 Democrat participants. The demographic information of the participants is presented in Table 6.1.

Our best results came from the "ideologically clean" set of participants. We looked at the analysis from two aspects:

Figure 6.1 Facial Action Units

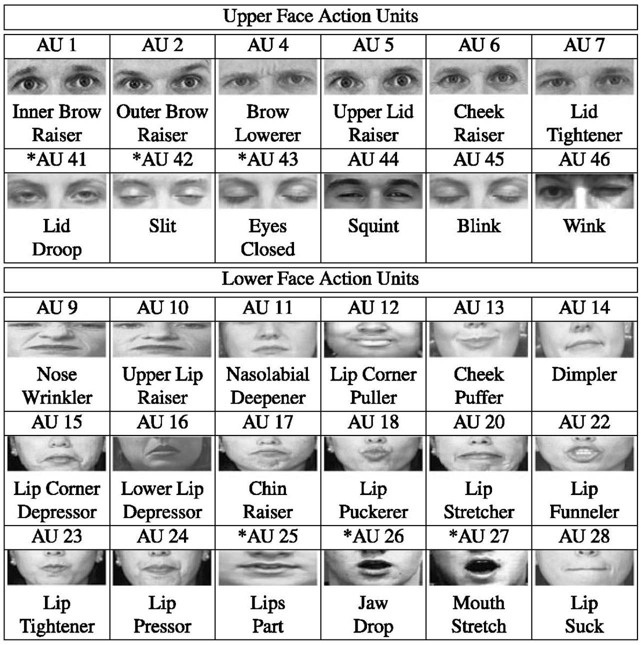


Table 6.1 Demographic information of participants

	Republicans	**Democrats**
Gender	6 Males 4 Females	3 Males 10 Females 1 Other
Pro Life	7 Yes 2 No 1 Other	1 Yes 12 No 1 Other
Pro Healthcare	2 Yes 7 No 1 Other	13 Yes 1 Other
Pro Police	10 Yes 0 No	1 Yes 12 No 1 Other
Pro Gun Control	1 Yes 9 No	10 Yes 2 No 2 Other

1) Can we predict affect experienced by participants from the political affiliation of candidates?
2) Can we predict the political affiliation of the candidates from the 7 streams of affect data that we segregated.

In Fig. 6.2 to Fig. 6.5 you can see that for both Democrats and Republicans, disgust increases and valence decreases when watching videos of an opposing politician say things they disagree with, as compared to the condition where they both align with the politician and agree with the content of what is being said. Republicans appear to have a larger total swing in both signals, which we hypothesize is a consequence of President Donald Trump's loss in the 2020 elections.

Fig 6.2 Disgust regression coefficients

[21] Loria, Steven, et al. "Textblob: simplified text processing." *Secondary TextBlob: simplified text processing* 3 (2014).

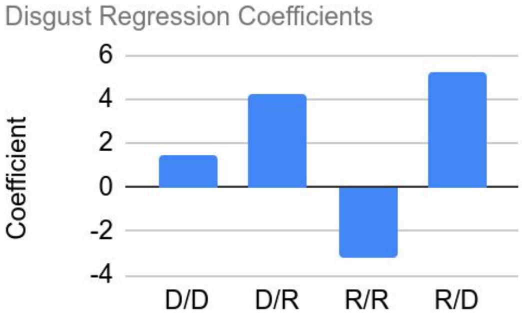
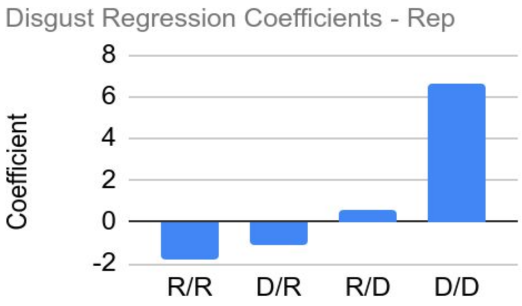
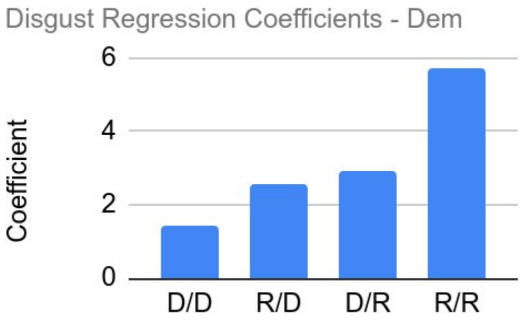


Fig 6.3 Disgust regression coefficients by party





In order to evaluate RQ1, we compare the regression coefficients across the four test conditions, controlling for party affiliation. The figures above show that the Republican subjects appear to exhibit a difference in affect between identity and ideology showing that someone from the other party saying something they agree with is treated more positively than the converse. Democrats do not show a significant difference between identity and ideology in their affective reactions. A complete listing of regression coefficients and p-values can be seen in Table 6.2

Fig 6.4 Valence regression coefficients

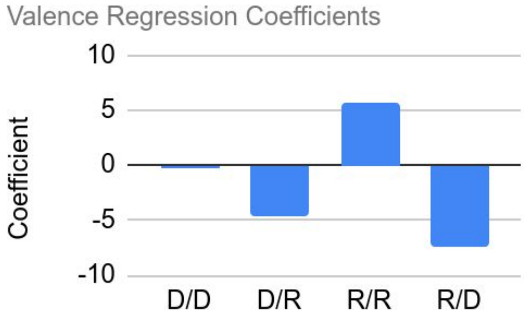
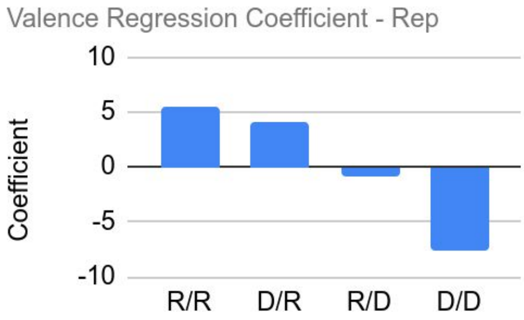


Fig 6.5 Valence regression coefficients by party



<u>Modelling affect as a predictor of identity</u>

The best regression model to predict party identification using measures of affect is composed of 'valence', 'engagement' and 'joy' as independent variables. This work is meant to reproduce the results of McDuff et al. 2013.[13] Positive coefficients indicate that higher values of the signal predict that the subject is a Democrat and vice versa. Interestingly, this model does not use the test condition to predict party, even when test condition is included as an interaction variable. This could be attributed to the limitations of logistic regression, however a Classification and Regression Tree (CART) model produces similar results with similar performance metrics as shown in Fig. 6.8

Fig. 6.6 - Variable Correlation matrix showing the multicollinearity between different affect signals

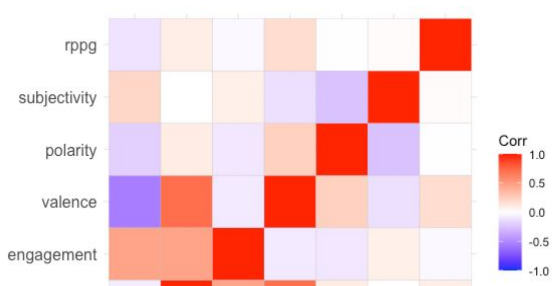


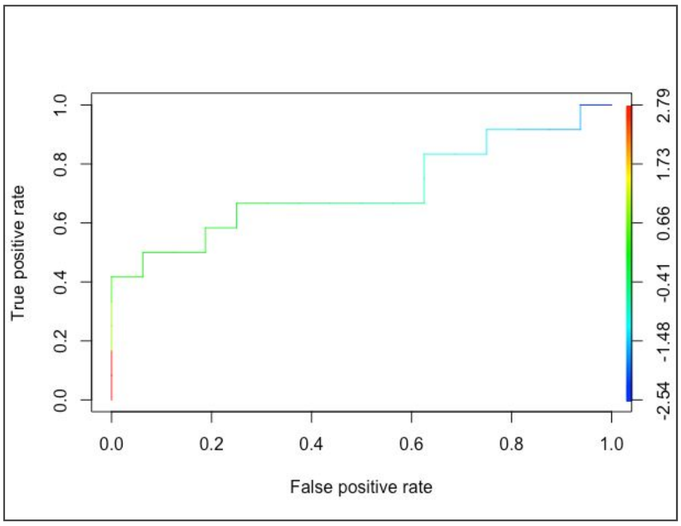
Table 6.2. All p-values are reported in comparison to the base case, which is a Democrat watching a video of Joe Biden supporting liberal policy.

Signal	Party	Condition (Identity / Ideology)	Coefficient	P-Value
Disgust	Democrat	(D/D)	1.46	N/A
		(D/R)	2.89	0.37
		(R/D)	2.58	0.48
		(R/R)	4.24	0.37
	Republican	(D/D)	5.18	0.12
		(D/R)	-1.10	0.73
		(R/D)	0.63	0.28
		(R/R)	-3.24	0.07
Joy	Democrat	(D/D)	3.54	N/A
		(D/R)	3.06	0.74
		(R/D)	3.12	0.77
		(R/R)	4.85	0.35
	Republican	(D/D)	3.50	0.99
		(D/R)	4.90	0.53
		(R/D)	1.07	0.30
		(R/R)	1.33	0.33
Engagement	Democrat	(D/D)	15.46	N/A
		(D/R)	16.27	0.78
		(R/D)	13.47	0.67
		(R/R)	19.51	0.16
	Republican	(D/D)	9.44	0.63
		(D/R)	13.86	0.87
		(R/D)	20.51	0.09
		(R/R)	16.79	0.74
Valence	Democrat	(D/D)	-0.22	N/A
		(D/R)	-2.10	0.50
		(R/D)	-1.93	0.49
		(R/R)	-4.70	0.11
	Republican	(D/D)	-7.47	0.19
		(D/R)	3.99	0.34
		(R/D)	-0.94	0.86
		(R/R)	5.69	0.19
Polarity	Democrat	(D/D)	20.25	N/A
		(D/R)	-9.03	0.04
		(R/D)	6.89	0.24
		(R/R)	-6.86	0.06
	Republican	(D/D)	2.49	0.24
		(D/R)	34.20	0.45
		(R/D)	38.58	0.31
		(R/R)	35.36	0.46
Subjectivity	Democrat	(D/D)	46.74	N/A
		(D/R)	54.49	0.33
		(R/D)	58.88	0.16
		(R/R)	63.07	0.07
	Republican	(D/D)	46.04	0.94
		(D/R)	58.69	0.30
		(R/D)	54.47	0.51
		(R/R)	24.97	0.10
rPPG	Democrat	(D/D)	20.78	N/A
		(D/R)	20.63	0.96
		(R/D)	21.56	0.80
		(R/R)	19.88	0.71
	Republican	(D/D)	15.24	0.22
		(D/R)	20.64	0.98
		(R/D)	21.13	0.94
		(R/R)	22.66	0.65

Table 6.3. Coefficients of the logistic regression model to predict party from affect

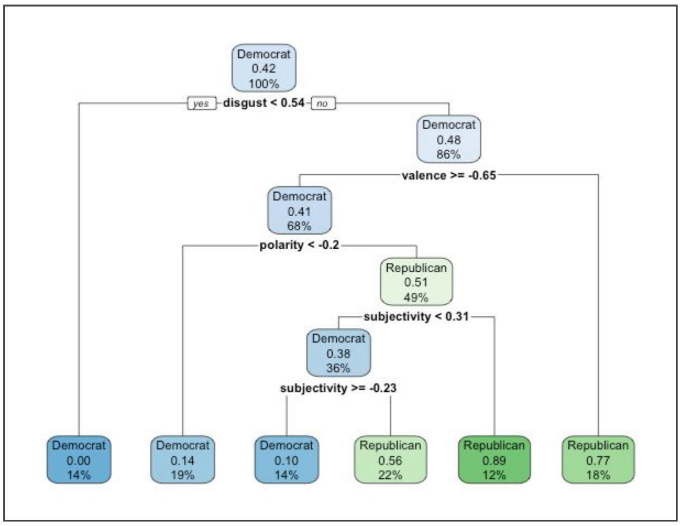
Signal	Coefficient	P-Value
Engagement	-0.101	0.009
Joy	-0.186	0.003
Valence	0.260	0.009

Fig 6.7 Logistic Regression ROC



The model reports an ROC area under the curve of 0.74.

Fig 6.7 Classification and Regression Tree (CART)



Discussion

We obtained the closest results to statistical significance from our first model, where we predicted the "disgusted" facial affect of subjects when watching political videos of politicians/ideologies they do not support. This result indicates the converse of our hypothesis, that subjects are more disgusted when presented with a *politician they identify with* expressing *views they disagree with* than they are when presented with a *politician they don't identify with* expressing *views they agree with*. Other affect signals paint a similar picture, but with higher variance that makes the results difficult to interpret.

Even with a small number of participants, however, we find that affect is strongly predictive of party affiliation. Engagement, valence, and joy are all statistically significant predictors given the conditions of this specific study.

Limitations

We modelled our dataset when there were 16 participants, and then again with 24 participants and noticed a measurable improvement in both predictive power as well as statistical significance. We think that we may be able to improve the strength of our findings if we extend our dataset to more participants, and are conducting a power analysis to ascertain the theoretical requirements to do the same.

We suspect that there may be demographic confounders in our data as well. For instance, it may be more socially acceptable for women to express emotion in the United States than it is for men. Those belonging to racial minorities or socioeconomic class may have a different reaction to issues around policing than other groups, in addition to party identity effects. Increasing the size of our sample will also allow us to segment by demographic in order to isolate some of these potential confounders. Luckily for us, the Affectiva SDK accounts for the presence of facial artefacts like glasses before providing a measure of the affective response.

Ideological defections, where Republicans or Democrats show choices that do not reflect our expectations of "party behaviour", for example where Republicans are Pro Choice or Democrats are Anti Gun Control, potentially introduce noise into our data. We will also be able to control for these issues better with more data.

Background affect was a noticeable confounder in some of our measurements. For example, we had Republican participants who expressed anger at the Democrats, when watching a video of Trump as a measure of solidarity.

Future Work

In the future, we will ensure that participants we recruit are ideologically aligned on all of the issues about which we show videos in order to isolate the effect of identity and ideology on affect as cleanly as possible. We will also separately analyze the explicit facial affect that participants expressed after each video, by manually isolating those video frames and passing them through the affectiva SDK when extending this work, for a more direct comparison between implicit and explicit measures of the affect.

We think this experiment could provide more insight, in the pure affective polarization sense, if participants are asked how a certain political video made them feel about members of the other party, and this question could be correlated with past work in this area.

It is unclear what the effects were of running this study so close to the presidential election. In future work we may run subjects during a quieter political landscape.

There is also potential for using the methods we propose from affective computing with methods generally seen in affective polarization like IATs, self reported surveys and economic games, to see how the models and results compare.

In a non-pandemic era, we strongly encourage the collection of physiological measurements using sensors attached to the body rather than rPPG, to improve the accuracy of the data.

We believe that the range of methods in affective computing can add a richer understanding to affective polarization.