Emotional Framing in U.S. Presidential Twitter Communication (2008–2023)

A Transformer-Based Analysis of Obama, Trump, and Biden

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1 Introduction

Emotions are central to political communication. They shape how citizens interpret events, evaluate leaders, and decide whether to participate in politics. A growing literature argues that political elites strategically deploy emotions to mobilise supporters, delegitimise opponents, and justify policy choices. Anger has been linked to increased political participation and polarisation; fear can increase support for security policies; hope, optimism and pride are often used to project competence and national unity.

At the same time, the communication environment of presidents has changed. Twitter provides a direct, unfiltered channel to millions of followers. President Obama pioneered the use of social media for campaigns; President Trump made Twitter his primary medium for political communication; President Biden inherited both the platform and an unprecedented series of crises, from the COVID-19 pandemic to democratic backsliding concerns.

This project investigates how three recent U.S. presidents: Barack Obama, Donald Trump, and Joe Biden, used emotional language on Twitter between 2008 and 2023. I focus on *emotional framing*: the way issues, actors, and events are described using emotion-laden words. I apply pre-trained transformer models fine-tuned on GoEmotions to classify emotions in tweets and examine how these emotions are distributed across time, topics, and rhetorical targets.

The contribution of this project is two fold:

1. Methodological: design an end-to-end pipeline that integrates data ingestion, transformer-based emotion classification, topic and target labelling, aggregation, and explainability (SHAP and attention heatmaps).
2. Substantive: provide a comparative analysis of emotional framing across three presidents, interpreting temporal patterns in light of major events such as the 2008–09 financial crisis, the 2015–16 and 2020 election campaigns, the Trump presidency, and the COVID-19 pandemic.

2 Research Question and Methodology

2.1 Research Questions

How do different U.S. presidents strategically employ emotional framing in their public communication on Twitter, and how does this vary across actors, topics, time periods, and political contexts?

Let's address several sub-questions:

(RQ1) Do campaign periods display more negative and mobilising emotions than presidencies?

(RQ2) Which emotions dominate each president's communication style?
(RQ3) How do emotions vary across policy topics such as economy, immigration, healthcare, and security?
(RQ4) How are emotions targeted toward the self, political opponents, policy issues, or other actors?
(RQ5) How do emotional patterns evolve over time in response to major events (elections, crises, protests)?
(RQ6) Can explainability methods highlight the specific words that drive emotion predictions, thus revealing rhetorical mechanisms?

2.2 Problem Formulation

Let each tweet be a text sequence $t_i = (w_{i1}, \ldots, w_{iL_i})$ with associated metadata $m_i = (a_i, d_i, p_i, \tau_i, \gamma_i)$, where:

- a_i is the actor (*Obama*, *Trump*, *Biden*);
- d_i is the timestamp;
- $p_i \in \{\text{campaign}, \text{presidency}\}$ is the phase;
- τ_i is the topic (economy, environment, foreign policy, healthcare, immigration, rights_justice, security, other);
- γ_i is the rhetorical target (*self*, *opponent*, *issue*, *other*).

I use a transformer model to define a function

$$f_\theta : t_i \mapsto \hat{\mathbf{e}}_i,$$

where $\hat{\mathbf{e}}_i$ is a probability distribution over fine-grained emotion labels from the GoEmotions taxonomy. These are then mapped into seven *key emotions*:

$\mathcal{E} = \{\text{anger}, \text{fear}, \text{pride}, \text{joy}, \text{sadness}, \text{optimism}, \text{gratitude}\}$

and an overall valence $v_i \in \{\text{positive}, \text{negative}, \text{neutral}, \text{neutral/other}\}$.

For any subset of tweets $\mathcal{S}$ defined by conditions on (a, p, τ, γ), I define the empirical share of emotion $e \in \mathcal{E}$ as

$$\text{Share}(e \mid \mathcal{S}) = \frac{1}{|\mathcal{S}|} \sum_{i \in \mathcal{S}} \mathbb{1}\big[e_i = e\big],$$

where $e_i = \arg\max_e \hat{\mathbf{e}}_{i,e}$. I compute such shares across actors, phases, topics, targets, and time to analyse patterns of emotional framing.

2.3 Methodology Overview

The project pipeline consists of the following components:

Step 1 Data ingestion
It ingest three CSV files containing tweets from Barack Obama, Donald Trump, and Joe Biden. Timestamps are parsed into a unified format and tagged as *campaign* or *presidency* based on each actor's electoral timeline.

Step 2 Pre-processing and balancing
Tweets are lowercased, URLs and user handles removed, and non-ASCII noise stripped. To keep computation tractable and avoid actor imbalance, we downsample each actor–phase combination to at most 1,500 tweets (`max_per_actor_phase = 1500`).

Step 3 Topic and target labelling
Use lightweight keyword rules to assign each tweet to one of eight topics (e.g. *economy*, *immigration*, *healthcare*) and one rhetorical target: self-referential tweets, attacks on opponents, issue-focused messages, and residual "other".

Step 4 Emotion classification
Employ the `DistillBERT` model (a BERT transformer fine-tuned on the GoEmotions

dataset). For each tweet we obtain probabilities for 27 fine-grained emotions and map them into seven key emotions plus valence (positive / negative / neutral / neutral-other).

Step 5 Aggregation and visualisation

Using the processed dataset, I compute emotion shares per actor, phase, topic, target, and month. It generate:

- stacked bar plots of valence by actor and phase;
- bar plots and heatmaps of key emotions by topic and by rhetorical target for each actor;
- time series of anger and fear, and of positive emotions (pride, joy, optimism, gratitude) by month.

Step 6 Explainability

To inspect how the model reaches its decisions, I apply SHAP to individual tweets and visualise token-level contributions as HTML force plots. I also compute attention heatmaps from the last transformer layer, showing which words attend to each other in emotional predictions.

3 Experimental Results

3.1 Data Overview

Table 1 summarises the approximate number of tweets for each actor after balancing.

Actor	Time span	Tweets (balanced)
Barack Obama	2008–2016	∼3,000
Donald Trump	2015–2021	∼3,000
Joe Biden	2018–2023	∼2,622

Table 1: Approximate size and coverage of the balanced Twitter dataset.

Tweets are tagged as *campaign* when posted before election victory and *presidency* thereafter. For Trump and Biden, the campaign period includes the intense 2015–2016 and 2019–2020 contests. For Obama, the campaign period covers the 2008 and 2012 elections.

3.2 Valence by Actor and Phase

Figure 1 shows the distribution of positive, negative, neutral, and neutral/other valence across actors and phases.

Several patterns emerge:

- Campaign periods are more negative than presidencies for all three actors. This is especially pronounced for Donald Trump, whose campaign tweets exhibit the highest share of negative valence.
- During their presidencies, all actors shift towards more positive and neutral tone. Obama's presidency remains strongly positive; Biden's presidency also shows a high positive share, consistent with a "return to normalcy" narrative after the Trump years.
- Trump's presidency retains a significantly higher negative share than Obama's or Biden's, reflecting a confrontational governing style.

These findings align with the expectation that campaigns incentivise attack messages and fear appeals, whereas presidencies require a more reassuring tone.

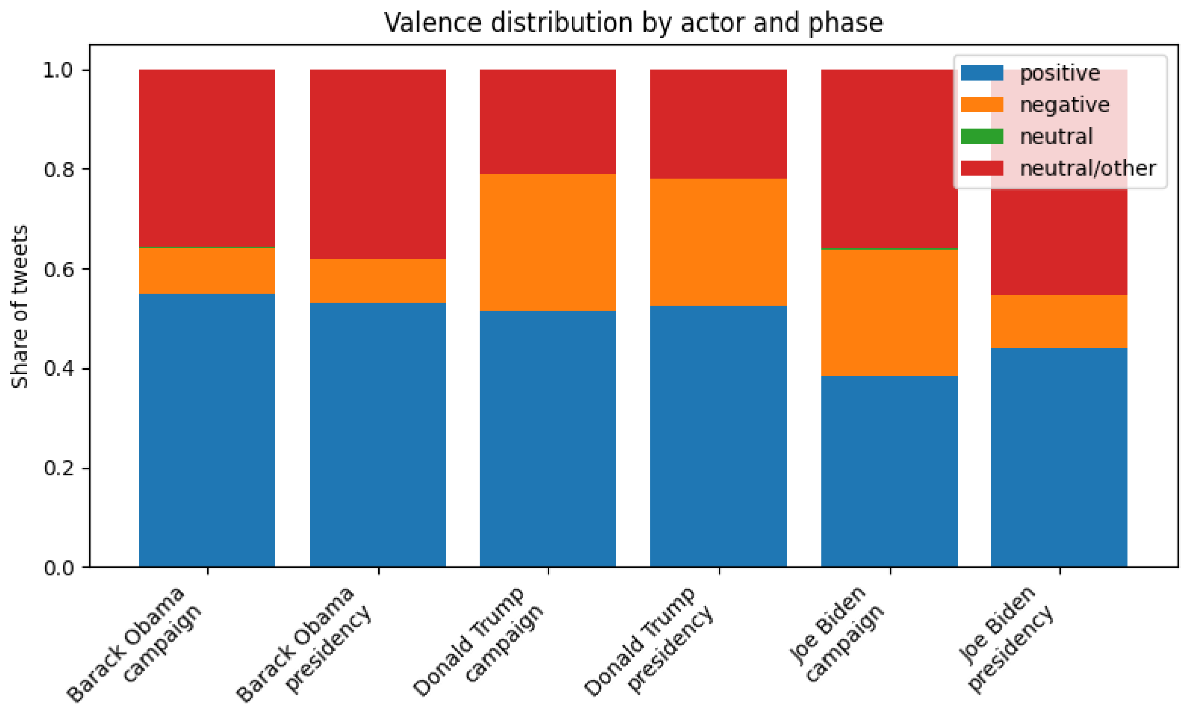

Figure 1: Valence distribution by actor and phase.

3.3 Key Emotions by Actor and Phase

Figure 2 presents the distribution of seven key emotions within the subset of emotionally non-neutral tweets.

Barack Obama. Both campaign and presidency phases are dominated by gratitude, optimism, and pride, with very low levels of anger and fear. Obama's communication style focuses on thanking supporters, expressing hope, and framing policy achievements as collective progress.

Donald Trump. Trump exhibits substantially higher anger than the other presidents, particularly in the campaign. Anger remains prominent during his presidency, especially when discussing opponents or contested issues. Gratitude is also present, often in messages praising supporters or policy victories.

Joe Biden. Biden's presidency shows notable levels of gratitude and optimism, but also increased sadness relative to Obama and Trump. This likely reflects the COVID-19 context, where mourning victims and acknowledging national trauma co-exist with optimistic messaging about recovery and vaccines.

3.4 Emotions by Topic

Topic-specific patterns are captured in Figures 3 and 4.

Key observations include:

- **Immigration and security.** Trump shows strong anger and sadness on immigration and security topics, consistent with his hard-line framing of border control and crime. Biden also displays anger on rights_justice topics, often in the context of threats to democracy or voting rights.

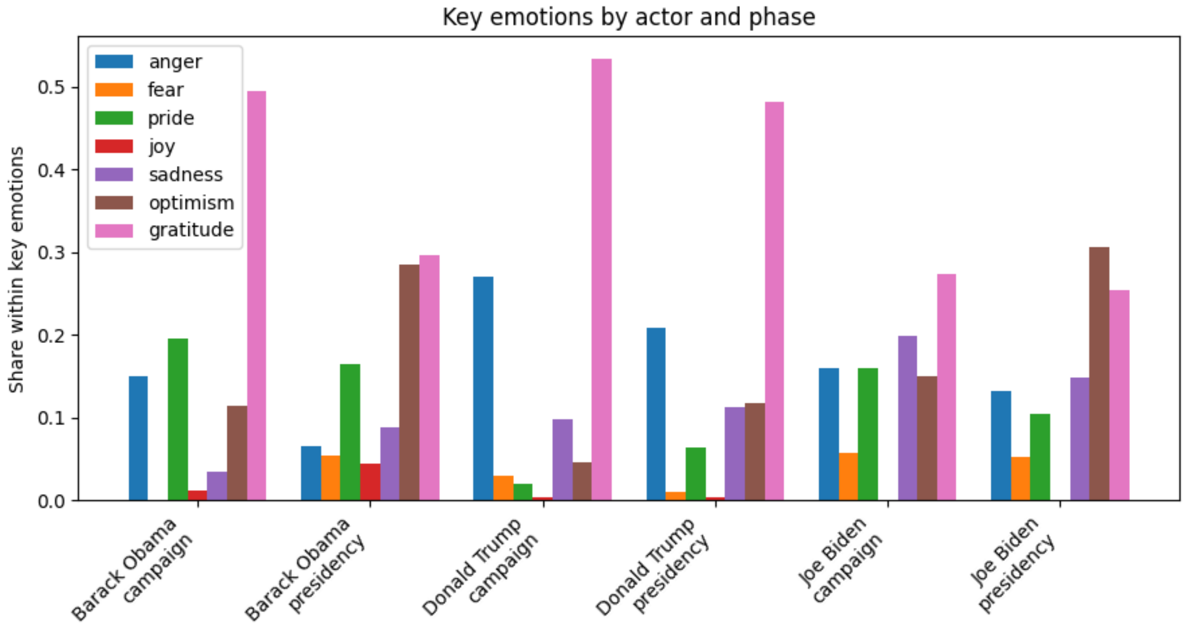

Figure 2: Key emotions by actor and phase.

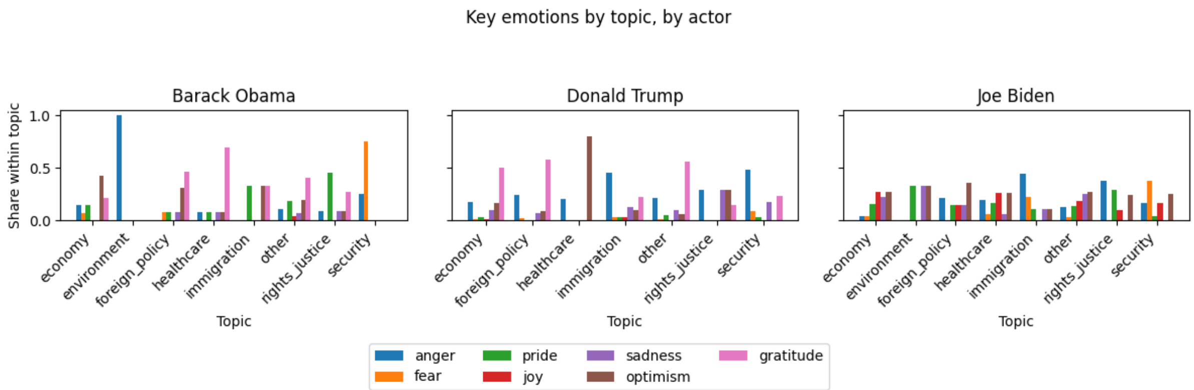

Figure 3: Key emotions by topic, by actor.

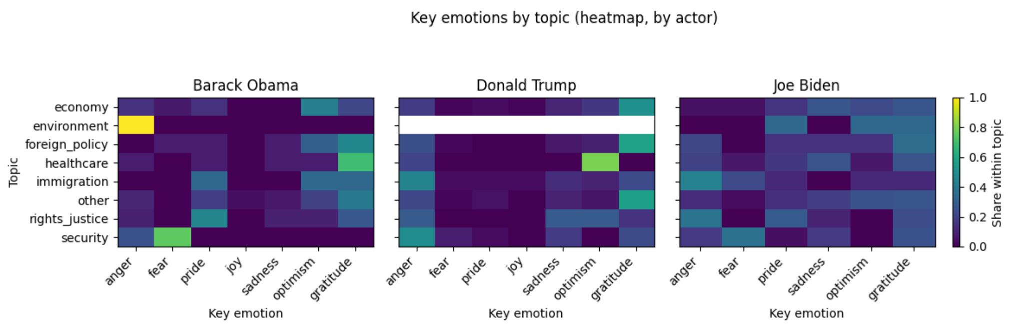

Figure 4: Key emotions by topic (heatmap, by actor).

- **Environment.** Obama exhibits high fear on environment, reflecting climate risk framing during debates on the Paris Agreement and environmental regulation. Trump has little emotional engagement with environmental topics in this dataset.
- **Healthcare and economy.** For Biden, optimism and gratitude are salient on healthcare and economy, especially during the vaccine rollout and economic recovery messages in 2021–2022.

These topic-specific differences align well with each administration's policy priorities and public agenda.

3.5 Emotions by Rhetorical Target

Figures 5 and 6 examine how emotions vary depending on whether tweets are directed at issues, opponents, the self, or other actors.

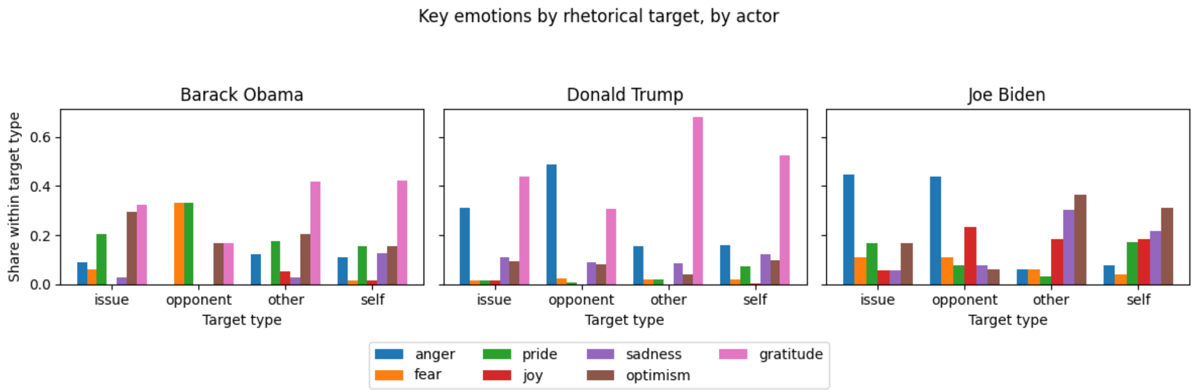

Figure 5: Key emotions by rhetorical target, by actor.

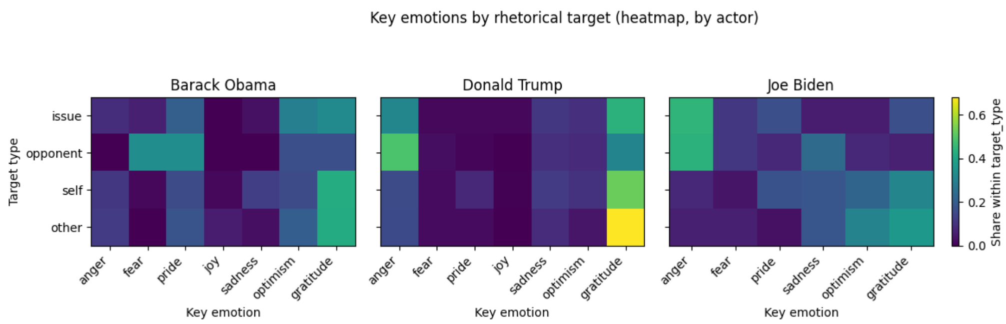

Figure 6: Key emotions by rhetorical target (heatmap, by actor).

The main pattern is that *anger is strongly concentrated on opponents*, particularly for Trump and Biden in campaign or highly polarised moments. Self-referential tweets are dominated by gratitude and pride for all presidents, e.g. thanking supporters or celebrating achievements. Issue-focused tweets show more fear (environment, security, pandemic) and optimism (policy proposals and plans).

3.6 Temporal Dynamics

Figures 7 and 8 show monthly time series of anger/fear and positive emotions (pride, joy, optimism, gratitude).

We can relate peaks and troughs to political events in the United States:

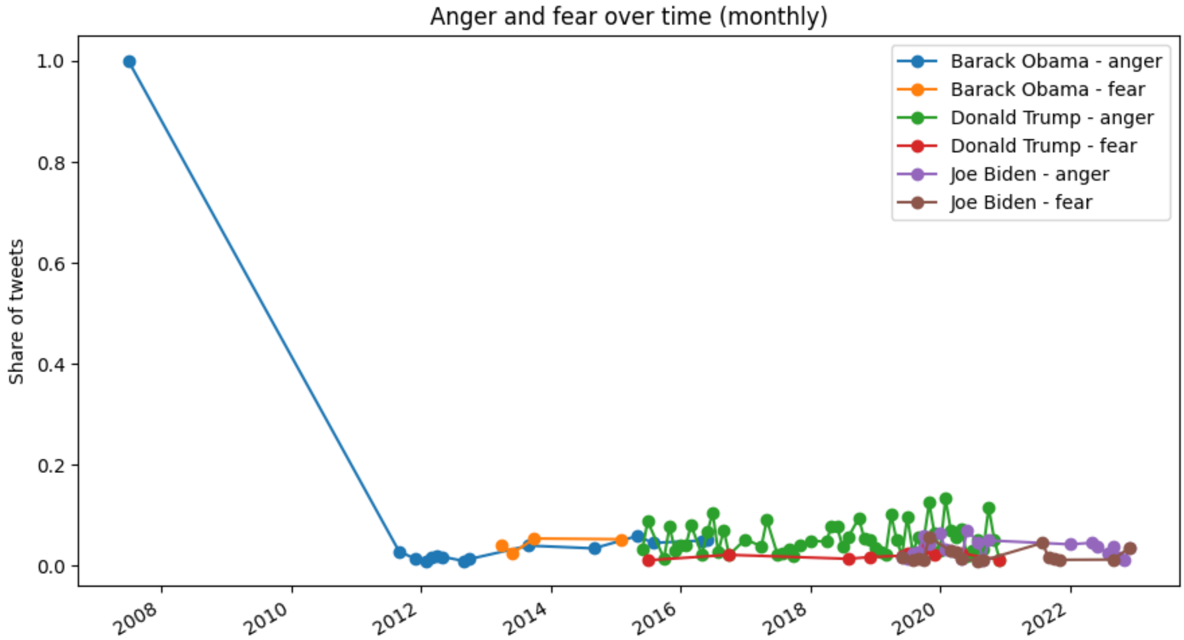

Figure 7: Anger and fear over time (monthly).

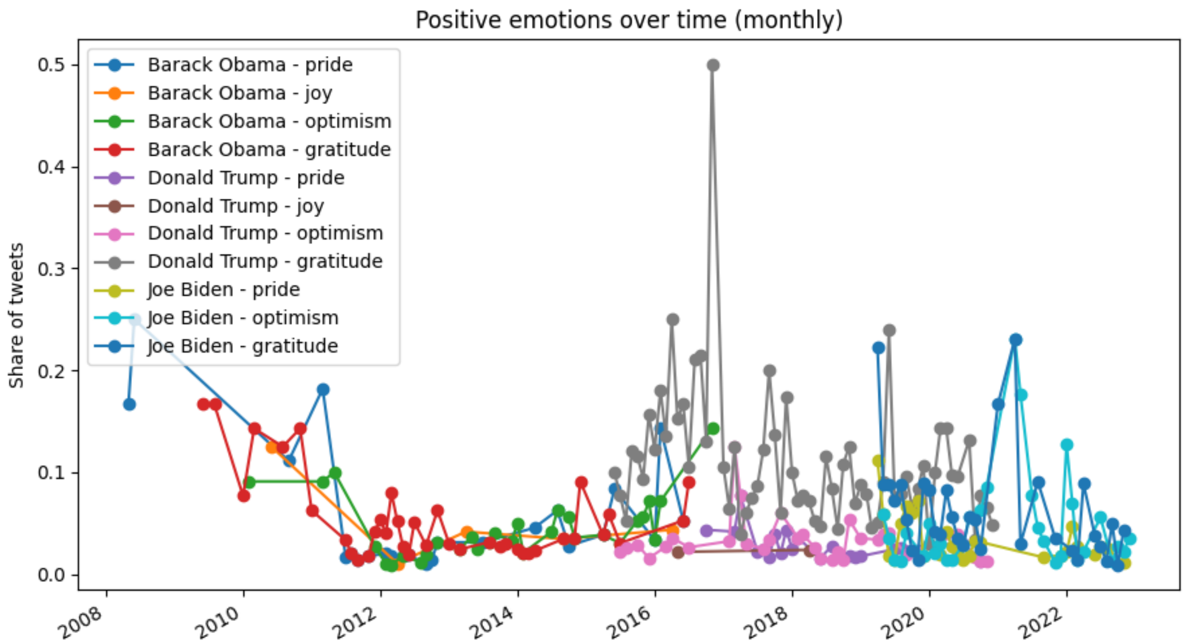

Figure 8: Positive emotions over time (monthly).

- **Obama.** Anger and fear are relatively low and stable after 2008. Occasional increases in fear coincide with debates on climate change and mass shootings, where Obama emphasised risk and urgency. Positive emotions remain high throughout his presidency, consistent with a unifying, hopeful rhetorical strategy.
- **Trump.** Anger displays large spikes around:
  - the 2016 election campaign and early presidency;
  - the 2017 travel ban and immigration controversies;
  - the 2018 midterm elections and the "caravan" narrative;
  - the 2020 election and its aftermath.

  These correspond to periods of intense polarisation and conflict, where Trump's messaging framed opponents and migrants as threats.
- **Biden.** Negative emotions (anger, fear, sadness) increase around the 2020 election, the January 6th attack, and the height of the COVID-19 pandemic. Positive emotions, particularly optimism and gratitude, rise during the vaccine rollout and economic recovery announcements in 2021–2022, reflecting an attempt to project competence and hope.

Overall, the temporal analysis shows that emotional framing responds to real-world crises and political stakes: anger and fear escalate during contested elections and security crises, while optimism and gratitude dominate phases of policy success or stabilisation.

Explainability: SHAP and Attention

To validate that the model is responding to meaningful emotional cues, we inspect SHAP explanations for selected tweets.

First, consider a Trump tweet from the presidency phase:

> *"Employment is up, Taxes are DOWN. Enjoy!"*

For this message the model assigns a relatively high probability to *joy*. The SHAP force plot shows that words such as *"Employment"*, *"up"*, *"DOWN"* and especially *"Enjoy"* strongly increase the joy score, while function words and punctuation have almost no effect. The explanation is consistent with a celebratory, self-congratulatory frame that links economic success to a positive emotional appeal.

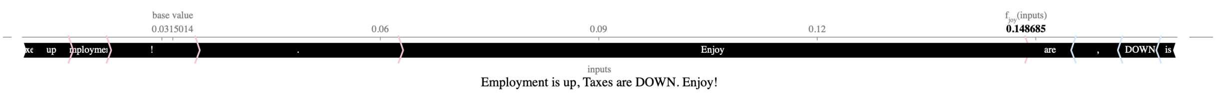

Figure 9: SHAP force plot for a Trump presidency tweet classified with high *joy*.

A second example comes from a Biden tweet during the presidency, mobilising voters in Georgia:

> *"Georgia, today is Election Day—and the eyes of the nation are on you. Head to the polls and help send @USER back to the U.S. Senate."*

Here the model predicts an elevated probability of *anger*. SHAP highlights phrases such as *"Election Day"*, *"eyes of the nation"*, and *"on you"* as key contributors that push the anger score upward, while more neutral connective words pull the prediction back toward the baseline. The explanation reflects a morally charged call to action that frames the election as a high-stakes moment, using pressure and implied outrage to motivate turnout.

Attention heatmaps for these and other tweets confirm that emotionally salient words (e.g. *"Employment"*, *"DOWN"*, *"Enjoy"*,*"Election Day"*, *"eyes of the nation"*) attract strong attention from the classification tokens, suggesting that the model focuses on intuitive emotional triggers rather than spurious artefacts.

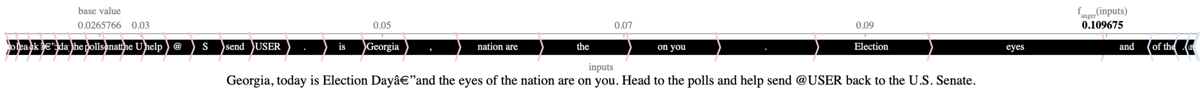

Figure 10: SHAP force plot for a Biden presidency tweet with elevated *anger*.

4 Concluding Remarks and Future Work

4.1 Summary of Findings

This project demonstrates how transformer-based models can be used to analyse emotional framing in political communication. By combining GoEmotions-based classification with topic and target labelling, we obtain a detailed picture of how presidents deploy emotions on Twitter.

Key findings include:

- Campaign periods are systematically more negative than presidencies for all three actors.
- Obama relies heavily on positive emotions—gratitude, optimism, and pride—with minimal anger, reflecting a unifying rhetorical style.
- Trump uses anger far more frequently than Obama or Biden, especially when targeting opponents on immigration and security issues, consistent with populist mobilisation.
- Biden's presidency combines gratitude and optimism with notable sadness, corresponding to the COVID-19 pandemic and national mourning, and uses anger primarily when condemning threats to democracy.
- Topic- and target-specific heatmaps show that fear is tied to environmental risks and crises, anger to opponents and contested issues, and gratitude to self-referential or supporter-directed messages.
- Temporal trends align with major events: anger spikes during elections, policy crises, and institutional conflicts; positive emotions rise during periods of policy achievement and recovery.

These patterns suggest that emotional framing is context-dependent and strategic: leaders adjust their emotional tone in response to electoral incentives, crises, and governing responsibilities.

4.2 Limitations and Future Work

Several limitations offer directions for further research:

- **Single-platform data.** The analysis is restricted to Twitter. Extending to speeches, press conferences, and other social media would enable a broader view of presidential rhetoric.
- **Model bias and domain shift.** The GoEmotions model is trained on Reddit comments, which differ from presidential language. Future work could fine-tune on political corpora or human-annotated presidential text.
- **Causal inference.** We describe correlations between events and emotional patterns, but do not establish causal effects (e.g. whether emotional spikes influence approval ratings or media coverage). Linking emotions to polling and media data would be an important extension.
- **Cross-national comparison.** Applying the same pipeline to leaders in other countries (e.g. Italian prime ministers Meloni, Conte, Draghi) would enable comparative analysis of emotional strategies across political systems.

4.3 Conclusion

Emotion is not a side-effect of political communication but a strategic resource. By leveraging transformer models, this project shows how different presidents construct emotional narratives tailored to their political environment: Obama's hopeful mobilisation, Trump's angry populism, and Biden's mixture of mourning and recovery. The pipeline developed here provides a reusable framework for studying emotional framing in political discourse and can be extended to other actors, media, and languages.

AI assistance disclosure.
Parts of this project have been developed with the assistance of OpenAI's ChatGPT (GPT-4). The AI tool was used to support the generation of code examples and the structuring of methodological workflows. All content produced with AI assistance has been carefully reviewed, edited, and validated by me. I take full responsibility for the final content and its accuracy, relevance, and academic integrity.

References

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