Digital Visual Political Communication:
Social Media Imagery of the
2020 Presidential Election

A Thesis Submitted in Partial Fulfillment of the Requirements of the
Renée Crown University Honors Program at Syracuse University

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Spring 2020

Honors Thesis in Communications and Technology

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Abstract

The important role of social media in politics is changing the way digital visual political communication influences potential voters. Assessing what types of images are posted by politicians to their publics can create new ways to organize and analyze political messaging across social platforms. Exploring images posted on Instagram and Twitter by Democrat and Republican 2020 presidential election candidates during their campaign allowed for an extensive, diverse dataset; this dataset determines what politicians are sharing online and if human-based coding methods can combine with machine-based coding methods to determine larger visual attributes in political imagery. These human-based and machine-based assessments combine to form the hypothesis that images encouraging aspects of community are posted more often than other types of images.

Executive Summary

There's no shortage of communication throughout the lifecycle of an American presidential election. According to Merriam-Webster dictionary, the definition of *communication* can be described as "a process by which information is exchanged between individuals through a common system of symbols, signs or behavior" ("communication," n.d.). Campaign communication is achieved through many measures, including advertisements, in-person visits and – as popular in the 2020 presidential election – social media.

Social media helps to create a new form of voter: a participatory media user. Individuals can claim more control over the messages they see and interact with on social media, allowing for more direct communication between a candidate and their publics. In networking sites that encourage participatory media behavior, imagery is often used by political campaigns to sway potential voters. Two of these popular image-sharing social media sites are Instagram and Twitter. This exploration was designed to answer the following questions about political social media imagery: If these images can be sorted under certain characteristics by a human, will the addition of computer-found labels in a photo be able to reasonably indicate presence of larger visual classifications? What are 2020 politicians visually posting to their viewers?

This project was separated in two parts to assess categorization. The first was focused on human-based categorization and the second employed machine learning (the study of algorithms that improve with, and learn from, experience). The sample used for these tests were images from Instagram and Twitter posted by 2020 presidential election candidates from January 29, 2019 until October 23, 2019. All in all, images from 12 candidates were assessed from

Instagram, and 29 candidates on Twitter. Images were not connected to their candidates' handles, captions or comments during characterization.

Human-based coding assessed four different kinds of classification: content, medium, aesthetic, and authenticity. A codebook was developed to explain more: content classification discerns the 13 options for the subject of the image, medium classifications defined the seven types of images that could be shown, aesthetic classification assessed four ways color could be depicted and authenticity classification had two options to assess image formality. This codebook was applied to 427 images; each was assessed under all four classifications.

Computer-based coding in the likes of machine learning created a second layer to this exploration. A program using Google's Image AI Label Detection API (a pre-made machine learning algorithm program produced by Google) was utilized. This program took an image as input and listed the top ten labels Google identified for the image. Accuracy ratings for each perceived label were also included. This application was tested on 374 images and the top ten labels for each image were recorded.

Both findings from human- and computer-based coding combined to create valuable insight to the social media images of politicians in the 2020 presidential election. Most notably, the majority of both types of methods found that aspects of community were a primary focus of political imagery in this context. In the hand-coded data, the top labels of "community" and "crowd leader" combine to make up 41.68% of the entire data, a stark majority amongst 13 total classifiers. The machine-coded data identifies labels of "community" and "event" labels identified from Google Vision combine to describe 81.55% of that dataset. All of these labels describe aspects of community in significant percentages of the database, lending truth to the idea that “community empowerment is virtually government policy” (Shaw, 2006). It’s evident that digital visual political communication is mostly focused on community.

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Acknowledgements

This project was heavily influenced and guided by Syracuse University School of Information Studies Professor Dr. Jennifer Stromer-Galley. Her unique studies of political communications in the information age sparks interest in many of her students to explore social landscapes more. Thank you for your time, dedication, patience and undying leadership.

Another heartfelt thank you to Dr. Regina Luttrell of the Public Relations department of Syracuse University's S.I. Newhouse School of Public Communication as lending her expertise as a reader. It's amazing to have cooperative parties from both of my academic homes on campus lend their talents to this piece.

An additional thank you to Alexander Owen Smith, a Ph.D. student at Syracuse University's School of Information Studies, for his assistance. His help on first-time academic writing, research techniques and experiment lifecycles made this project possible. Thank you for your commitment, supreme interest and inspiring love for information studies.

A cornerstone of my collegiette academic career has involved research in conjunction with the School of Information Studies. Starting by assisting with research to substantiate a government-funded intelligence technology project as a sophomore, I thoroughly enjoyed learning through the many technology sectors these studies could reach; our work penetrated facets of human-computer interaction, user experience, design and social computing. While I began with a limited mindset to the lessons learned to come from being a research assistant, each task encouraged me to remain inquisitive.

Eventually, my research area shifted to personal interest in visual media and digital emotion, leading to my current project exploring digital visual political communication. For the majority of 2019 I have been enthralled with the dynamic political race for the upcoming 2020 presidential election. This sparked questions of voter's perceptions of candidate-created social media content, the differences between traditional print and new-aged digital political messaging, and the categorization of political imagery put forth on platforms like Instagram and Twitter.

I enjoy this topic because of the sincere unknowns that influence both political and social media alike. In both cases, even one influencing event can completely change trends and metrics that used to be secure; a political scandal can ruin a candidate's chance for office while a brand's misstep on social media can have a direct influence on their economic success. The unpredictability is compelling, and – happily, in my own self interest – simply provocative and never dull to study.

Through this research I am able to utilize my two majors in technology and public relations to study the apex of political social media messaging. The topic of digital visual political communication mashes two unpredictables together to create volatile insight to what's in the eyes of the voting public and what inferences are perceivable from this information. This research aims to properly classify the meaning behind visual messages, but along the way I hope to understand what weight digital visual political communication serves to voters at all.

Advice to Future Honors Students

A collegiette journey, imagined even before stepping foot on your college campus, is a scribble of opportunity and possibility. It's not until you're in your final months that you truly begin to straighten the scribble into a pathway. This pathway can, truly, lead anywhere you'd like it to. Don't worry if your scribble is, well … too scribbly. It'll straighten, or even just reduce curves, to become a pathway you can see. However, the most amazing part is that it was a pathway all the time. Everyone on that scribble, who helped you through the scribble, or who advocated for your scribble is part of your pathway forevermore. Thank them, and hold them close.

Introduction

Social media creates instantaneous, personal connection between the public and political candidates. This fosters the ability for any social media user to interact with a campaign and to, in turn, become a direct target of political messaging. Specifically, with image-sharing social media networks like Instagram and Twitter, candidates can personalize their message, which draws dedicated followers, likes, comments, and shares.

There has always been interest in visual political communication, starting from the television-politics relationship secured in the 1960s (Corcoran, 2014). The current decline of television-based politics and the rise of internet-based social networking expands the ability for campaigns to use different types of images to influence voters (Gurevitch, 2009). Knowing what types of images are being shared is an important factor in being able to study the effect of digital visual political communication on potential publics. This project was designed to answer the following research questions: 1. Knowing that political images can be classified by significant attributes in content, medium, aesthetic and authenticity, will the combined presence of machine-found labels in a photo be able to reasonably indicate presence of larger visual attributes? 2. What are 2020 politicians visually posting to their viewers?

To explore these research questions, over 500 unique images from Instagram and Twitter accounts of 2020 presidential election candidates were evaluated through both human- and machine-based coding methods. Using a grounded content analysis approach, images were evaluated on the basis of content, medium, aesthetic and authenticity. Images were also run through the Google Vision AI application programming interface to be classified by noun-based labels. When assessed together, the importance of community in political social media imagery is evident in top-scoring labels like “crowd leader” and “team,” affirming that politicians are carefully crafting depictions of community online to bolster their community in real life.

Background

Political Imagery

Choosing to study at the intersection of social media and politics is both timely and important. The role of visuals in communication is a well-researched aspect of communication that humans passively learn and are exposed to throughout their lifetime (Debes, 1968). The sharing of visuals in media is a mix of both “communication” (two-way one-to-one or one-to-many messages) and “information” (one-way obtaining of knowledge or data that makes a difference), as defined by Schroeder (2018). Visuals are assessed by an audience in a similar manner to textual information; under the title of “visual rhetoric,” the 1970s scholarly decision included imagery in the study of rhetoric, where only verbal discourse was previously studied (Smith, 2004). To create ultimate “frames” that can organize and give meaning to any type of message (Arowolo, 2017). This is done through a sequence of selective perception/structuring, decoding, the construction of relations and, finally, their integration into coherent meaning (Geise, 2015). These frames, heavily aided by visuals, help to introduce audiences to politicians and their messages, both textual and visual. As Rose (2001, p. 6) believes, “the visual” is key in the “cultural construction of social life in contemporary Western societies.”

Political communication and marketing were established early on in American politics (Corcoran, 2014). In the 1960s, the earliest political imagery popularity of political television created a popular media model to research and gauge effect on potential voters. Since then, rapid technological change and the rise of digital information has influenced change on how political imagery and the frames it creates are assessed (Mutz, 2015). Before the popularization of the world wide web in the 1990s, many political researchers idealized years of political television influence as the best medium for political campaign communication (Press, 2015) (Kaid, 2020). The rise of the internet and social media have obviously changed political messaging engagement forevermore (Van Praag, 2017). Now, potential voters using social media to engage in politics are active in "participatory media;" individuals can claim more control over the media they see and interact with (Nakamura, 2014), specializing the frames these individuals choose to develop on the politicians they've chosen to engage with. This is in line with Grunig and Hunt's (1984) third of four public relations models, two-way asymmetrical communication, redefined by Dozier, Grunig and Grunig (1997) as a model used to "help organizations persuade publics to think and behave as your organization desires" (p. 12). This communication is driven by research on the publics approached. Even as participatory media opens the door for two-way communication, technology-driven political communication (today's social media) emphasizes the most important aspect of two-way asymmetrical communication: "appeals are made directly to the public through the mass media by experts in electronic communication; and sophisticated and scientific methods such as polls, computers, direct mail, and television are used to make these appeals" (Alexander, 1969, p. 257). The digitization of political communication is important because it allows information to be synchronously forwarded to new publics in a timely fashion (Wang, 2018).

Although dramatic changes in the media landscape have changed how potential voters are digesting and interpreting political imagery in this participatory way, the importance of these images are still evident. Current participatory social media is designed with the idea of “flow,” a psychological ideal created to move users from one element to another and unfocus on lengthy engagement, in mind (Bolter, 2019). Because a photograph is often regarded as a form of evidence, social media imagery’s flow nature encourages consumers to analyze quickly, compounding the range of layers one political image could convey (McDonald et al., 2016, p. 180).

Nonetheless, politicians are aware that the power of imagery, coupled with the ease of social media sharing, strongly suggests that digital visual political communications are effective in themselves without attached text. McDonald et al. (2016) go as far as to posit, “Social media represents a significant acceleration in the possibility that communication itself can become more visual, in the sense that it is now possible to hold something very close to a conversation that is almost entirely without voice or text” (p. 177). This means that images have just as much weight on their public, if not more, than other political messaging (Schill, 2012). In one study of political imagery spread on social media, Edgarly et al. (2016) found that 98.5% of community-shared posts contained an image. Because of this focus on visuals in social media, political campaigns heavily weigh imagery in their ability to craft a frame and share a story (Liebhart & Bernhardt, 2017). Likened to the need for a good story to propel a book or movie, literature claims voters will be more likely to engage with politicians when they are involved in the politicians’ narrative through engaging imagery (Liebhart & Bernhardt, 2017). Because a politician has the unique ability to control their own imagery frame more accurately than the media-led framing in other outlets (like mass print media or news television), a self-owned platform is arguably the most distinct location to accurately craft and share a message (Miller, 1998). Stromer-Galley (2000) stated that internet platforms are only utilized by politicians for two reasons: to provide controlled, highly crafted information about the candidate, and "to provide a façade of interaction with the campaign and the candidate through media interaction" (p. 127). The top-down, one-way controlled model was evident in political advertising on television in the 1960s, the rise of the internet in the 1990s inspired controlled personal messaging online, and today's social media is a self-crafted political story in a voter's pocket (Kaid, 2020; Grunig et al., 1984; Stromer-Galley, 2000; Liebhart, 2017).

Computational Techniques

Imagery is difficult to analyze because of its complex impact on the human mind. Gamson et al. (1992) writes "reading media imagery is an active process in which context, social location, and prior experience can lead to quite different decodings" (p. 375). Additional depth of analysis is necessary to create universal imagery frames. In juxtaposition to the human-based coding of visual content analysis, computer-based coding falls under the umbrella of aspects granted by the power of *computation*. While the meaning of computation has changed over time, from the one-time popular definition derived by mental mathematical computations, it now overwhelmingly relates to the use of machines for computation (Denning, 2010). Computation in the digital age is exciting because it provides the ability to deeply analyze data, far more than human-based exploration can infer. Machine learning is part of this computation that provides valuable data quickly and efficiently. Defined as "the study of algorithms that improve with, and learn from, experience," (Mitchell, 1997, p. 14) machine learning is a computational approach to reaching far beyond basic computing power and compounding that initial power. The specific subset of machine learning with research prowess is deep learning, currently heavily utilized in computer and speech recognition, natural language processing and autonomous vehicles (Yapici, 2019). It's the artificial intelligence basis of deep learning that allows for such strong computations. In this exploration Google Vision AI's label detection API was used as a machine learning tool for deep learning in a subset called computer vision, the field that concerns how computers interpret images (Paul, 2018).

While deep learning is provocative, problems with artificial intelligence remind researchers that utilizing methods of both human- and computer-coded information is preferable. Technochauvinism, the belief that technology is always the answer, can undermine researchers' otherwise cautious approach to adopting novel and unvalidated methods to pursue social research (Broussard, 2019). To combat the over-reliance on technology, using both human and machine methods to assess visual communication is important.

Methods, Data Collection

Content analysis is a research methodology often used to analyze unstructured messages to understand their meanings; in the case of this exploration, images are necessarily unstructured, since there is often little metadata or "structure" for quantitative analysis. This technique is cited for "making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use" (Krippendorff, 2004, p. 18). Images are meaningful matter that can be analyzed with this method because they have meaning that can be categorized and analyzed. Imposing analytical categorization on images changes supposed meaning into empirical assessment. This exploration is a grounded theory approach because it works with a "discovery of theory from data—systematically obtained and analyzed in social research" (Glaser, 1967, p. 1). It's exploratory and derived from research of the datatype itself, a primary qualification for grounded content analysis. Adhering to Rose's interpretation of visual materials, images are to be assessed only in groups that are exhaustive, exclusive and enlightening (Rose, 2001).

The samples used for content analysis were images posted by 2020 presidential election candidates on official campaign accounts on Instagram and Twitter in 2019. As Instagram and Twitter are social networks that connect tens of thousands of people around the world, it's evident that political outreach on these sites will impact the public in some way. Both of these services support image sharing as a primary feature.

Instagram Data

The first batch of hand-coded data was collected by manual labor on Instagram. The sample size was comprised of 12 of the candidates actively running in the 2020 presidential election as of April 2019. These candidates were composed of the incumbent Republican, Donald Trump, and 11 other social Democrat candidates: Elizabeth Warren, Julián Castro, John Delaney, Kirsten Gillibrand, Beto O'Rourke, Bernie Sanders, Erik Swalwell, Tom Steyer, Kamala Harris, Andrew Yang, and John Hickenlooper. Each candidate had an Instagram page devoted to their political life and/or campaign. For each of the 12 candidates, ten posts were assessed in reverse-chronological order from the first post posted on April 12, 2019. All posts were publically available on the Instagram webpage on public accounts. In this batch, 120 images were assessed independent of captions and comments.

Twitter Data

The second batch was collected from images posted on Twitter. This was achieved by scraping all the appropriate accounts for images using R. Each image can be recollected at the particular tweet level using the Tweet ID. The image group was compiled on October 23, 2019. The group contains 400 images. The collection was started on January 29, 2019 and holds images from any announced 2020 presidential candidate from the time of their exploratory announcement until October 23, 2019. The accounts accessed were those of Bernie Sanders, Beto O'Rourke, Andrew Yang, Terry McAuliffe, Richard Ojeda, Tulsi Gabbard, Jay Inslee, Mitch Landrieu, Elizabeth Warren, Wayne Messam, Kamala Harris, Bill de Blasio, John Hickenlooper, John Delaney, Seth Moulton, Kirsten Gillibrand, Tim Ryan, Erik Swalwell, Steve Bullock, Cory Booker, Julián Castro, Donald Trump, Pete Buttigieg, Amy Klobuchar, Joe Biden, Marianne Williamson, Michael Bennet, Joe Walsh and William Weld. All images were assessed independent of captions and comments. After being compiled, images from the second batch were saved in Google Cloud Platform Storage.

Methods, Human-Coded Data

This research utilized a grounded approach to content analysis, developing classifications of politicians' digital images meeting Gillian Rose's standards for content analysis (Rose, 2001). The classification of images was organized into four facets: content, medium, aesthetic, and authenticity. Within these facets, each classification met Rose's standard for exclusivity. Each image was assessed in all four categories, independently of scores in the other categories. Four iterations of the classification codebook determined the most viable categories to appropriately classify the majority of the images.

Several iterations of potential image behavior to be coded created the exhaustive, finalized codebook. While these categories were developed on Instagram, the sample candidates' accounts on Twitter showed many of the visual posts on Twitter to be similar or the same. Because of this, images from both platforms were analyzed together. Cross-platform images were coded in the same manner, but increased volume of sample images created greater divide between images that could easily fall into the first iteration's categories and those remaining in the "other" categories.

Content Classification

The content of an image discerns what is within the image, or the "subject" of the image. This classification aims to generalize the "big idea" of the photo from what it depicts most clearly. Coding was decided with the most-represented subject (or lack thereof) instead of a mix of all instances in an image.

Figure 1

Leader Picture

Note. Example of "leader picture" in content classification.

Realizing that the majority of images contained the politician themselves, content classifiers were mostly decided by the position of the politician within the image. One of the major classifications is the "leader picture," defined as showing a politician behind a podium or on a stage. They are the highlight of the image and can either have an assembled crowd shown or not, depending on the angle of the image shown. With this instance, the politician is leading a group with words or actions. Commonplace images that would fit the "leader picture" classification is of politicians speaking at rallies, addressing a congregation, or utilizing some kind of personal amplification device (megaphone, microphone, etc.).

Figure 2

Family/Community Picture

Note. Example of "family/community picture" in content classification.

Another important content classification is "family/community engagement." This shows a candidate interacting with individuals or groups. This is similar to the "leader picture," but does not show a definite focus on the politician. These types of images have a balance of all people in the photo. Most types of images that show this type of engagement show community group photos with a politician, the politician involved in community events or visiting community-shared places. Family and community engagement were combined because I could not immediately and positively discern images of the politicians family without any text present. In addition to this, it was made evident that a familial community bond is created between politicians and their publics so that the similarities are indistinguishable between a picture of a politician with their family and a politician with their community.

Figure 3

Ceremonial Picture

Note. Example of “ceremonial picture” in content classification.

A classification of “ceremonial” images was also used in this content analysis. Defined as any image that is explicitly religious, gives thanks, praise, pays tributes, honors, or expresses condolences, these include photos of obvious supporters without the candidate present. Many of these pictures depict themed parades, rallies for the candidate or holiday celebrations. As text comments were not available to check the sentiment of the image message posted in conjunction with the image, many of these images were double-checked against the basis of the "family/community engagement" classification.

Figure 4

Call to Action Picture

Note. Example of "call to action picture" in content classification.

Although a different feel of image from the others, the "call to action" classification is also important in content classification. This image type was defined as an image that implies the audience should act towards a specific political issue, event or cause. Most of the time these images included text that actually urged the audience to action. These images could ask supporters to join the politician for a rally, support another public official or urge action on another cause.

Combined, 13 unique content classifications were assessed. A full list of content classifications can be found in the Appendix.

Medium Classification

The second category, medium classification, defined what type of image was being shown. This was a difficult section to classify because many of the images assessed could have been coded with different categories of medium classification; in this case (for instance, in the case of different photos and medias being stitched together to create a new image), the main focus of the newly-created image (in the frame of viewing what was posted on social media) was coded. It was decided that video stills would not be included in the image analysis because the full medium could not be assessed from a cover picture. The finalized medium classifications were picture, modified picture, screenshot, comics, non-original picture, illustration and other.

Figure 5

Picture

Note. Example of “picture” in medium classification.

A picture (unmodified photograph) was an important classification in this section. This type of image did not have anything added onto it and was not internally altered in any way. This image could have been taken on any camera and uploaded with no changes. The image type is simplistic.

Figure 6

Modified Picture

Note. Example of "modified picture" in medium classification.

A modified picture was also coded for. This is defined as a photograph changed with text, obvious color filters, or other graphical elements and media. There was some kind of addition between the taking and the sharing of the photo that designated an "impure" photograph. The creation of a new image out of other images or media is considered a modified picture.

Figure 7

Illustration

Note. Example of “illustration” in medium classification.

A final important medium classification is “illustration,” another name for marked infographics. Politicians increasingly utilize digital political infographics to engage and persuade their publics. Past theory states that these types of images beg to be included in modern-day political theory due to the three trajectories that create a meaning behind these images; Amit-Danhi and Shifman (2018) explain “politicizing” infographic traits, “infographing” political tactics, and the combination of “tactile data experience” to create a new type of image.

This classification of “illustration” includes both text- and numerical-based infographics that blend characters and images to create something new.

Combined, seven unique medium classifications were assessed. A full list of medium classifications can be found in the Appendix.

Aesthetic Classification

Aesthetic classification focused on the colors associated within the image. Codes were assigned for instances of black and white images, images utilizing the candidates’ primary party color, images utilizing the opposition’s color, and “other” for those with no noticeable color schemes. While black-and-white images were easy to discern, choosing between a primary utilization of a purposeful main color and no color scheme was difficult. Images with a primary focus color had to have an overwhelming use of that color through the image. The assigned color for the Democratic party was blue and the Republican party was red. Later iterations of the codebook leaned away from primary party color representation because metadata disclosing the party of the posting politician was not available.

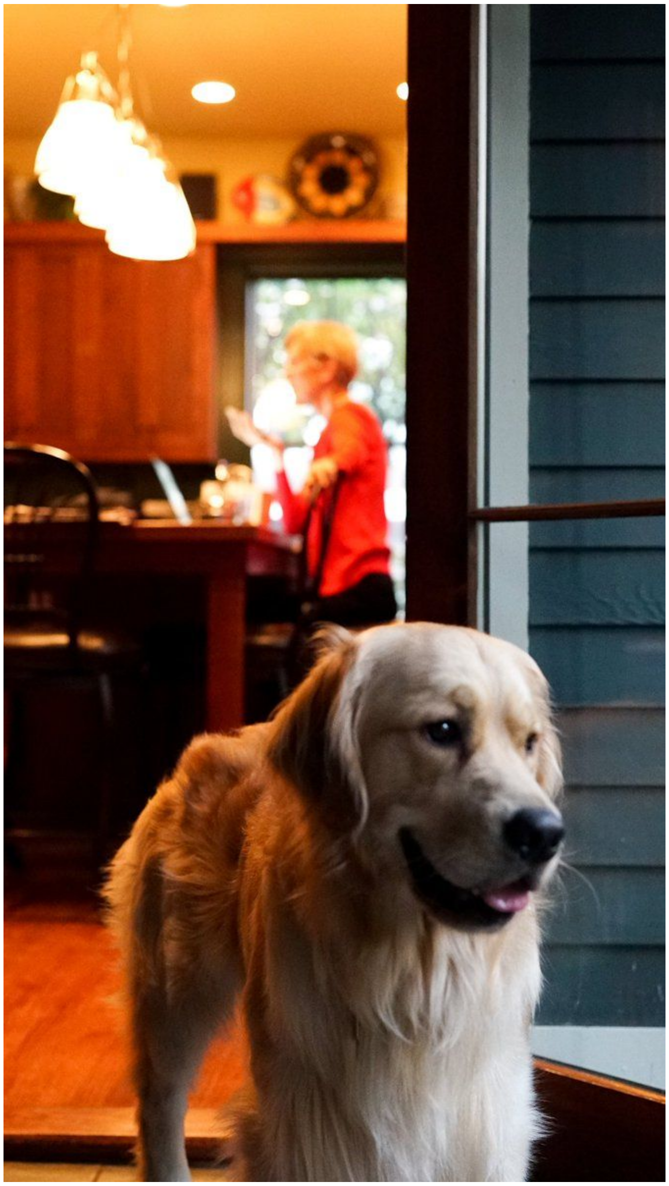
Combined, four unique aesthetic classifications were assessed. A full list of aesthetic classifications can be found in the Appendix.

Authenticity Classification

Authenticity classification pertains to if the image in question was of high or low quality; this quality relates to the categories of formal and informal imagery.

Figure 8

Formal Imagery



Note. Example of “formal imagery” in authenticity classification.

Formal imagery was defined as majorly clean, unblurred and indicative of staging. Images of this type were most likely produced with professional equipment. Images were deemed formal if they were superimposed with formal branding, included infographic messaging or was another sort of digital creation.

Figure 9

Informal Imagery

Note. Example of "informal imagery" in authenticity classification.

Informal imagery was less staged and of lower resolution. Pictures were occasionally blurry. Screenshots of other mediums besides pictures are considered informal imagery.

Methods, Machine-Coded Data

Machine Learning Selection

This project originally intended to fully utilize self-created machine learning algorithms to characterize and find specific labels across the Twitter data set. Many different combinations of deep learning software and coding platforms were considered. The three main options were Keras built on TensorFlow, PyTorch built on Caffe2, and VisionAI in Google Cloud Platform's shell.

Keras was attractive because it supported both convolutional and recurrent networks. These are two popular kinds of machine learning algorithms consisting of neural networks, maps of learned information inspired by the connected neurons of a brain (Nigam, 2020). These neural maps create layers of information that compound to create a machine's ability to accurately use the layered information to make predictions on new data. Convolutional neural networks (CNN) are important in computer vision services and imagery; an input is filtered by convolutional filters to create a supposed output. Recurrent neural networks (RNN) have a similar usage but are more often utilized for natural language processing (Nigam, 2020). Keras, with the ability to perform both CNN and RNN, has a clear, simple layout with hefty online documentation to help a beginner through their first neural network. As an abstraction layer (a layer of the neural network itself), Keras directly pulls from ResNet50, a 50-layer-deep pretrained model that recognizes millions of images from the ImageNet database with thousands of images for each noun in the known WordNet hierarchy. Using TensorFlow in conjunction with Keras was considered because Keras is already built into TensorFlow and can handle lots of data at the same time.

Another option was using PyTorch built on Caffe2. This pairing was attractive because of the many pretrained models that needed less data to personalize machine learning needs for this project. Also, different Python extensions allowed for clear segmentation of machine learning processes, which is great for beginners who want to build off of other models. PyTorch runs the image recognition software Facebook uses for mediating and tagging all photos sent through their platform, so it's known for power and agility.

The Google-based Vision AI was the final product heavily considered this was a hybrid version between creating your own model and using trained APIs. All images are sourced through the Google Images database, providing more insight as to where else the image might have accrued online and under what pretext. Many different versions of the API could be called to develop insight on different aspects of the images, including picking out famous landmarks, celebrities, and text analysis. The most compelling part of Vision AI was the label assigning feature that shows the top Google Image-defined attributes and their perceived accuracy rating.

API Selection

Google Vision AI was ultimately selected for the accuracy and depth of the API. The ability to interchange different versions of the API to find more information from the images promised many different potential outputs of the image analysis. Also, Google Vision AI was free for the first 1,000 images of each month, so the code could be repeated with different groups of images over time. The easy-to use Google functionality made a first-time project more manageable.

Another reason Google Vision AI was chosen was to utilize the proprietary intersection of Google Cloud Storage, the Google shell, and Google Vision AI. API access can be shared within the system to ensure cross-compatibility. Storage is guaranteed through personal Google accounts, ensuring that this exploration could continue long after University email access was lost.

Code creation

After deciding on using Google Vision AI, iterations of the final code were revised for months. The process to create a first machine learning experience was helped by an assortment of online tutorials, refresher coding courses, interpersonal assistance, professor guidance and crowdsource knowledge websites. Although many of the Google features tout their ease of use and set-up, several pieces of this exploration created roadblocks to hurdle over. Although the label-assessing part of Google Vision AI has an educational website to show how to use the API, there were few end-to-end examples a beginner could look to.

The first challenge was activating the Google Cloud Shell to start writing using Python. A computer directory problem did not allow my Google-assigned API key to be accessed or accepted by the shell, disallowing the API to run over the images saved in Google Cloud Storage. Also, anything created within the shell could not be saved to be rewritten later. Because of these problems, the exploration was moved to creation in Google Colaboratory, an in-line Jupyter notebook creation platform with cloud storage and many coding languages available.

The primary Google Vision AI labelling structure was described using the Google Shell, proving set-up in Google Colaboratory as another hurdle. Utilization of StackOverflow crowdsource community coding pages tackled problems like authenticating the Google Cloud

Services command-line features, account use, API and client key. Once all of the set-up problems were eradicated, manipulating the general API for uses specific to this exploration was much more manageable.

One of the most exciting parts of this project was the “building block” approach given to code creation. Through each iteration of the actual actionable block of code, new tweaks changed everything from input style to looping mechanisms, data collection to output style. Starting with a generalized copy and paste code provided by the API usage guide gave an outline to get the label detection application to run, but it was important that the code was updated to reflect best practices for this precise project. To create the finalized lines of code, short updates were added to each iteration of the building block. Over time these updates combined to create a code that addressed every personalized need the singular-use API didn’t originally contain. It was exciting to watch the iterations come together over time and frustration.

Early versions of the code printed the top 10 labels with the highest accuracy ratings for each photo. The code had to be run for each photo, changing the Google Cloud Storage URL of where the image was stored each time. The output was not saved and couldn’t be easily compared with the output of other images.

Figure 10

Google Vision AI Output, Version 1

```
def imagelab(image_uri):
  client = vision.ImageAnnotatorClient()
  image = vision.types.Image()
  image.source.image_uri = image_uri

  response = client.label_detection(image=image)


  for label in response.label_annotations:
    a = (label.description)
    print(a)
    b = (label.score*100)
    print(b)

[18] imagelab('gs://theyallkeepbitingthedust/data/DVskPPvVMAA1Ew0.jpg')

Outerwear
71.7257559299469
Event
69.42809224128723
Smile
64.1064703464508
Jacket
51.004964113235474
```

Note. This code was created in Google Colaboratory Notebook.

In order to visualize any of the findings from the labels of these images, the outputs had to be saved in a location where all of the findings could be seen together. Google Colaboratory saves associated files within the code notebook, so it made sense to write the outputs into a text file so more exploratory commands could be run on the file easily. The output was designed to print each image's top 10 labels, in order from most to least accurate, on a line that also included the ID name to link to the actual image. Spacing was added to ensure a human could also read and analyze the file.

Another change that was made was in the looping of the code itself. Instead of having to manually change the URL location of the image each time and re-authenticate through Google Cloud Storage, the function was created to always map to the Storage bucket where the images are. The input was changed to ask the user for a specific image ID easily copied from the Storage bucket, eliminating the need for a URL.

Figure 11

Google Vision AI Output, Version 2

```
[ ] def imagelab(image_uri):
      client = vision.ImageAnnotatorClient()
      image = vision.types.Image()
      image.source.image_uri = image_uri

      response = client.label_detection(image=image)

      for label in response.label_annotations:
        end = []
        a=(f'{label.description} ({label.score*100.:.2f}%), ')
        print(a)
        end.append(a)
        endfile = open("yay2.txt","a")
        for i in end:
          endfile.write(i)
      endfile.write(name)
      endfile.write('\n')
      endfile.close()
      print(a)
    name = input()
    imagelab('gs://theyallkeepbitingthedust/data2/' + name)
```

```
DdLw8F1VAAAt5ax.jpg
Restaurant (89.31%),
Building (80.25%),
Room (74.44%),
Café (73.38%),
Coffeehouse (72.98%),
Interior design (70.00%),
```

Note. This code was created in Google Colaboratory Notebook.

During scraping, the batch of Twitter data was randomized and mixed so that analyzed images could not be immediately connected to any account owner or caption. Three hundred and seventy four images in all were run through the program to find the top ten attributes of each.

Findings

Human-Coded Data

The first batch of Instagram data (consisting of 120 images) was compiled with a random 307 images from the Twitter batch to become a separate section of 427 images to be hand-coded according to the originally created codebook. As photos from neither Twitter nor Instagram showed any particularly independent qualities from each other, the decision was made to combine both groupings for analysis.

For each image, codes were assigned for all four categories (content, medium, aesthetic and authenticity). There were overwhelming majorities discovered through the analysis. Most images posted by politicians on Twitter and Instagram had content depicting community through an unedited, informal photo with no noticeable political color scheme.

Table 1

Human-Coded Data Content Analysis Findings

Classification	1st Most Popular Code	Percentage	2nd Most Popular Code	Percentage
Content	Community	25.76 (110 images)	Crowd Leader	15.92 (68 images)
Medium	Unedited Photo	55.03 (235 images)	Screenshot	7.02 (30 images)
Aesthetic	Other	85.94 (367 images)	Black and White	4.44 (19 images)
Authenticity	Informal	53.62 (229 images)	Formal	46.37 (198 images)

Note. The most popular attributes out of 427 hand-coded images.

Machine-Coded Data

Running a word count Python dictionary over the resulting .txt files revealed the top-used labels for each of the batches. All of the labels that were captured had a confidence level of at least 50%. The most frequently-found labels centered strongly around a focus on people.

Table 2

Machine-Coded Data Findings

Label	Amount of Images Containing Label	Percentage of Images Containing Label
Event	219	58.55
Community	86	22.99
Font	78	20.85
Crowd	69	18.44
Text	64	17.11
Team	58	15.50
Job	47	12.56
People	47	12.56
Room	39	10.42
Youth	38	10.16

Note. The most popular attributes out of 374 machine-coded images.

"Event"

The label "event" was the most-used characterization found through image recognition. In all, 219 out of 374 images were thought to be events; this is 58.55% of the dataset and depicts a perceived gathering of people. Sixty unique images cited "event" as the most-probable category.

Figure 12

Event, Image 1

Note. This image contains an “event” with 90.10% accuracy.

Figure 13

Event, Image 2

Note. This image contains an “event” with 91.95% accuracy.

“Community”

The second most popular label among the dataset was “community.” Of the 374 images, 86 (23%) contained a depiction deemed “community.” Of those, 11 images had “community” as its most likely attribute.

Figure 14

Community, Image 1

Note. This image contains “community” with 91.61% accuracy.

Figure 15

Community, Image 2

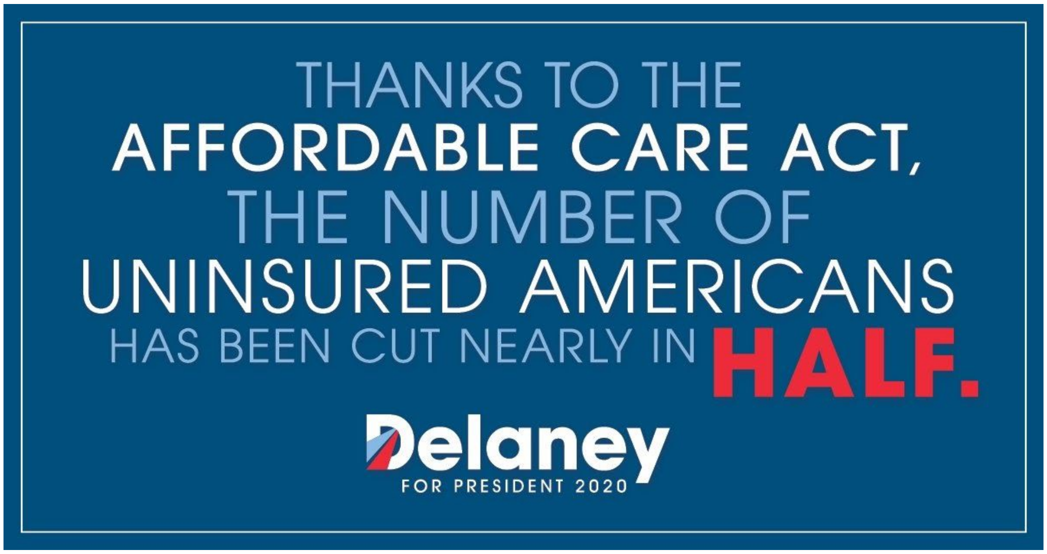
Note. This image contains "community" with 90.30% accuracy.

"Font"

The third most popular label identified by Google Vision AI was "font." Of the 374 images, 78 (20.85%) had a top ten label of "font." Of those, 10 images showed "font" as the most likely attribute. Many of the images containing a positive label of "font" can be cross-checked with the human-coded data codebook to be alternatively labeled as an "illustration," or infographic. The "font" of these types of infographics indicates text is the primary focus of this image.

Figure 16

Font, Image 1



Note. This image contains "font" with 97.11% accuracy.

Figure 17

Font, Image 2

Note. This image contains "font" with 93.57% accuracy.

Comparison

Similarities between the human- and machine-coded data clearly arise. The top labels of "community" and "crowd leader" combine to make up 41.68% of the entire hand-coded data in the content classification area, a stark majority amongst 13 total classifiers. Likewise, the "community" and "event" labels identified from Google Vision combine to describe 81.55% of that dataset. With tens of thousands of labels available through the API, this is a significant finding. These attributes can map together to place importance on community in political social media imagery. Many of the other popular labels from both the human- and machine-coded labels revolve around the idea of community. Throughout all of the 427 human-coded images, there were less than 10 images of politicians alone with no discernable political message, suggesting that a focused message is important in political social media imagery. This is backed up by the machine-coded data; so many of the most popular labels ("event," "community," "crowd," "team," "people," "youth") indicate the presence of many people rallying around a certain idea or candidate, furthering the conclusion that community might be the most important visual to portray in social media imagery.

Additionally, the other machine-identified popular label of "font" is important in furthering an idea of community. This label is majorly used to characterize infographics. Some scholars believe that infographics can form a sense of community by creating a link between knowledge producers (the politicians) and knowledge users (the public) (Otten, 2015). Using new media to create interesting ways to share political information can draw new people to join a political community. However, infographics are also used to persuade voting publics on political issues. Harvard Business Review states that an important part of an infographic's persuasiveness is in the relationship it forms: “You want to show someone something, but you also want to give them a sense that they’re free to move around and find their own relationships. When they do, they’ll have confidence that you really are giving them the whole story” (Ovans, 2016). The confidence and persuasive nature of an infographic between knowledge producer and knowledge user can be perceived as a method for community-building.

Conclusion

The 2020 presidential election has had an especially provocative presence on social networking sites. In this digital age candidates are expected to connect, share and interact with potential voters all over the nation. Online images in particular encourage interaction so they are commonplace in online campaigning. To explore what kind of images candidates are drawn to posting online, both human- and computer-based coding methods aided in classifying images according to what’s found in the image. Using a grounded content analysis approach, hand-coding identified unique images on the basis of content, media, aesthetic and authenticity. Using the Google Vision AI API, unique images were identified with top-confidence labels. Through both of these methods it was found that images that show aspects of community, including “crowd leader,” “event,” “team,” and “people” were much more popular than other image classifications. As prior research has been done to conclude that “community empowerment is virtually government policy,” (Shaw, 2006). it makes sense that the majority of the images posted for a campaign would be in conjunction with creating an online community through visual reinforcements of a physical community.

Being able to assess what politicians are posting in their digital visual political communication through the election cycle is important for several reasons. Firstly, knowing what types of images are being posted creates the ability to accurately and completely classify images in a comprehensive database. Because we can identify what we believe politicians are or will post in the future, classifications can help journalists, researchers, professors and other interested bodies quickly find visual political tools they need. Secondly, assessing social media images and text together can be done by mapping image classifications to known political text classifications to create new comparisons in social networking political influence. As social media companies continue to be "... salient news providers in all countries," (Kennedy, 2018), maintaining a way to properly classify digital visual political communication is ever-important for political cycles to come.

Next Steps

This research can be expanded to include many other variables. Primarily, studying images shared through other visual political communication services outside of Instagram and Twitter can add to the validity of political image assessments. Exploring images from Facebook, Tumblr and Pinterest can draw a larger sample size and the ability to differentiate types of images from different platforms.

To help to explain the soft conclusion of this work, further exploration of the definition of "community" can be achieved through output from different Google Vision AI APIs. Other abilities include being able to discern if a politician is present in a unique image, face and emotion detection, logo detection and image properties. Any of these APIs would be instrumental in analyzing many aspects of political imagery and finding changes and continuities amongst politicians. For instance, using the image properties service can show all of the prominent colors in an image; this can relate back to the "aesthetic classification" from the content analysis to draw new comparisons on what politicians are posting ("Features List").

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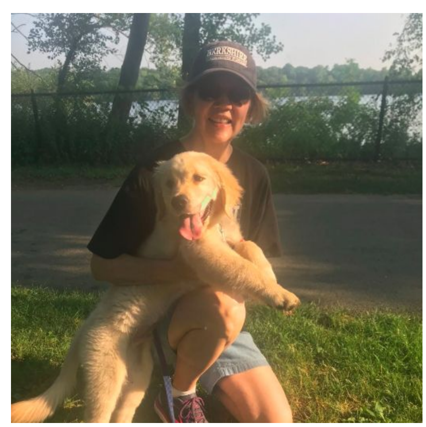
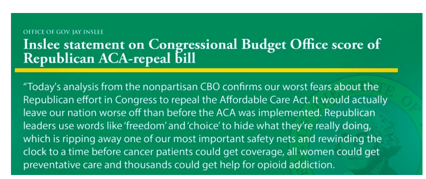
Appendix

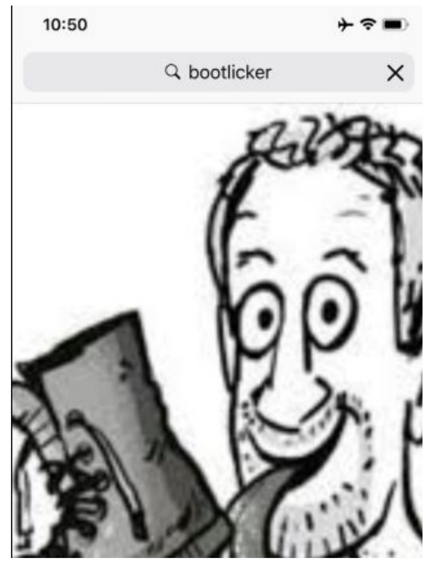
Complete lists of the codebook used to assess images for the human-coded data portion of this exploration are included for clarity.

Content Classification

	Classification	Definition	Example
1	Leader Picture	Politician behind a podium or on a stage with a group of people.	 https://pbs.twimg.com/media/DfXGNWCUcAAdlcH.jpg
2	Call to Action	Implying the audience should act towards a political issue or event.	 https://www.instagram.com/p/BsuBnjMlFkI/?utm_source=ig_web_button_share_sheet
3	Influencer	Pictures with political peers, celebrities, or business leaders.	

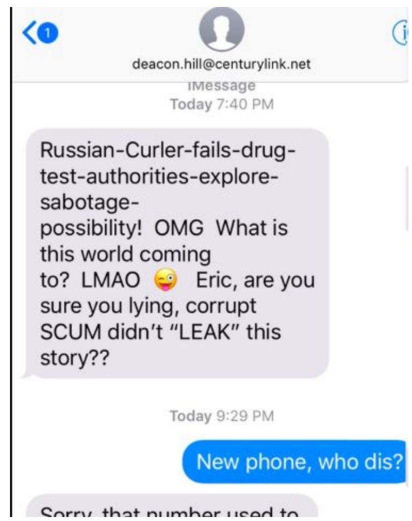
			https://pbs.twimg.com/media/DADnVwDW0AcX3p4.jpg
4	Family/Community Engagement	Candidate interacting with individuals or groups.	 https://pbs.twimg.com/media/DkAXtU5VsAAt6r4.jpg
5	Influencer Single Portrait	Same as Influencer Shots, but the account owner is not presented in the picture.	 https://pbs.twimg.com/media/DTl5kK5VoAIlK5z.jpg
6	Kids	Pictures of kids (with or without candidate).	 https://pbs.twimg.com/media/C3DN9XWVcAAV1nk.jpg
7	Pets	Pictures of pets (candidates' own or community).	 https://pbs.twimg.com/media/D

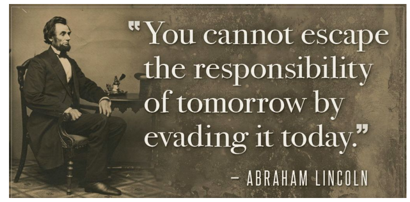
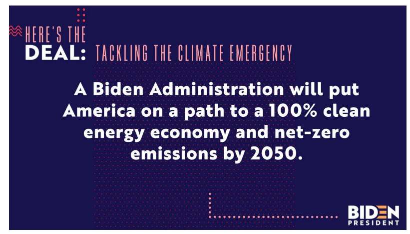
			-5gZBnWsAAnL7I.jpg
8	Ceremonial	Any image that is explicitly religious, gives thanks, praise, pays tributes, honors, or expresses condolences. Includes photos of obvious supporters without candidate.	 https://pbs.twimg.com/media/DTdR6iQXUAA-ts6.jpg
9	Uniform	People in professional uniform (assigned uniformity).	 https://pbs.twimg.com/media/D_Zr7w4XoAAM6rR.jpg
10	Alone	Image of candidate alone with no discernable political message.	 https://pbs.twimg.com/media/D6PQeO9W4AE_nvQ.jpg
11	Statement	Quotes from candidate or other.	 https://pbs.twimg.com/media/C61YzkXU8AEjHvN.jpg

12	No recognizable humans or animals	Focus is not the people, animal or words.	 https://pbs.twimg.com/media/DQTZ9w5XcAI81GC.jpg
13	Other	Image doesn't fit in with other classifications.	 https://pbs.twimg.com/media/D_MyaPvXYAInO2Z.jpg

Medium Classification

	Classification	**Definition**	**Example**
1	Picture	An unmodified photograph.	 https://pbs.twimg.com/media/DrQ4dg8WkAAYuGs.jpg

2	Modified Picture	Photograph that has been modified with text, obvious color filters, or additional media.	 https://pbs.twimg.com/media/DtdSSgxUcAASPFt.jpg
3	Screenshot	Screenshots of all digital mediums and traditional news outlets (TV news, newspapers, etc).	 https://pbs.twimg.com/media/DWbU6XOW4AAchwr.jpg
4	Comics	Cartoon picture	 https://pbs.twimg.com/media/D-QpdpcWkAM2J9s.jpg

5	Non-Original Picture	Image not the intellectual property of the account owner or their team.	 https://pbs.twimg.com/media/DzOlmgiX4AASB8I.jpg
6	Illustration	With (infographic) or without text.	 https://pbs.twimg.com/media/EA2SVdPWsAEYdNl.jpg
7	Other	Image doesn't fit in with other classifications.	

Aesthetic Classification

	Classification	Definition	Example
1	Black & White	The image is only black and white.	 which racks up unnecessary and unfair fees and sometimes leads to the closure of the account.[3] The CFPB spent five years honing the Payday Rule, conducting research and reviewing over one million comments from all types of stakeholders: from payday lenders, to state regulators, to faith leaders.[4] This work produced a targeted and balanced rule that will keep many American families from falling into debt traps and gained the support of faith leaders and civil rights groups across the country. On January 16, 2018 – the day the rule was to go into effect – the CFPB announced that it "intends to engage in a rulemaking process so that the Bureau may reconsider the Payday Rule," and that it would "entertain waiver requests" from entities subject to the rule's requirements.[7] That announcement came just weeks after Mr. Mulvaney told reporters in December that, after a briefing with CFPB legal staff, he had concluded that only Congress could control the fate of the Payday Rule because "it was fairly far out the door by the time" he took control of the agency.[8] Two days after it suddenly reversed course on the Payday Rule, the CFPB filed notice in a trial court in Kansas to "voluntarily dismiss[][9]" its case against four installment lenders: Golden Valley Lending, Inc., Silver Cloud Financial, Inc., Mountain Summit Financial, Inc., and Majestic Lake Financial, Inc.[10] In the complaint the CFPB filed last April in the case, it alleged that these online installment lenders attempted to collect loans that were void under state law.[11] The loans offered by these companies had APRs between 440% and 950%, and were not appropriately disclosed to customers. Many states have laws governing installment lenders, including interest rate caps that are below the rates charged by these companies, making the loans void. The companies nonetheless attempted to collect in an abusive and unlawful manner. Likewise, on January 22, 2018, the World Acceptance Corporation announced in a press release that it had been informed by the CFPB that "the investigation into the company's marketing and lending practices ha[d] been completed.[12]" The CFPB had opened an [3] https://www.federalregister.gov/documents/2017/11/17/2017-21808/payday-vehicle-title-and-certain-high-cost-installment-loans [4] https://www.consumerfinance.gov/about-us/newsroom/cfpb-finalizes-rule-stop-payday-debt-traps/ [5] https://www.consumerfinance.gov/about-us/newsroom/cfpb-finalizes-rule-stop-payday-debt-traps/ [6] https://www.consumerfinance.gov/about-us/newsroom/cfpb-finalizes-rule-stop-payday-debt-traps/ https://pbs.twimg.com/media/DU5tUkoWkAAZkvT.jpg

2	Party Color	Focus is on GOP red (for a republican candidate) or Democrat Blue (for a democratic candidate).	 https://pbs.twimg.com/media/DpaAxl0VAAEehlv.jpg
3	Opposing Party Color	Focus is on GOP red (for a democratic candidate) or Democrat Blue (for a republican candidate).	 https://pbs.twimg.com/media/DqNJt7XW4AAbn98.jpg
4	Other	Image doesn't fit in with other classifications.	 https://pbs.twimg.com/media/DMYvQBzVAAAh9Nc.jpg

Authenticity Classification

	Classification	**Definition**	**Example**
1	Formal Imagery	Image is clean, unblurred, produced with professional equipment, and/or superimposed with formal branding. Includes infographics and other digital creations.	 https://pbs.twimg.co

			m/media/DgPhzDeXkAMSmMQ.png
2	Informal Imagery	Unclean, blurry, unstaged and/or unprofessional.	 https://docs.google.com/document/d/1yeuSvhOaf7zzkD8JHOR9cjoFmGEtM_HAGYn2QvwAxdI/edit