Measuring China's Propaganda Using Machine Learning on Images and Text

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1 Introduction

2 Visual Political Communication

In the contemporary, media-saturated age, visual communication has emerged as a leading form of expression, marked by the daily upload of 300 million photos to Facebook and 95 million to Instagram (Stout 2023). This age of ubiquitous imagery not only highlights our visual-centric culture (Hand 2012), but also actively shapes both personal identity and the social construction of reality (Aiello and Parry 2019; Stocchetti and Kukkonen 2011).

This visual shift has permeated politics, where images have become key tools for politicians to influence voters and communicate with the public (Farkas and Bene 2021; Grabe and Bucy 2009; Enli and Skogerbø 2013). Most citizens rely on media images to learn about elected officials and candidates, making visuals a primary means of constructing political perception (Graber 1987). In the constrained time available on television and other media platforms, politicians strategically use visuals and verbal symbols to amplify messages, controlling elements such as dress and facial expression to support arguments or guide perceptions (Schill 2009). As a result, information is now blending with entertainment, misinformation is increasing, and politicians are using visuals to deliberately craft self-images (Russmann, Svensson, and Larsson 2019; Enli and Skogerbø 2013; Haim and Jungblut 2021; McGregor, Lawrence, and Cardona 2017).

Although many scholars have highlighted the growing importance of visuals in contemporary political communication (Bauer and Carpinella 2018; Lilleker, Veneti, and Jackson 2019; Graber 1996), the primary focus has largely remained on textual elements, such as issue framing and the use of particular rhetorical strategies (Griffin 2001). Only in recent years has there been a marked shift towards visual aspects in academic studies of political communication (Barnhurst and Quinn 2012; Aiello and Parry 2019; Russmann, Svensson, and Larsson 2019). This trend has been bolstered by new digital technologies and datasets that have enabled more nuanced analysis of images (Williams and Gulati 2013; Weidmann and Schutte 2017). However, despite these advances, there remains much to learn about how political actors strategically use visual communication and how audiences in turn respond to this form of communication.

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2.1 How Effective Are Images as a Medium for Communication?

Visual communication plays a fundamental role in human understanding, cognition, and communication. Neurologists have highlighted the importance of images in shaping our perceptions and consciousness, emphasizing their role in developing self-awareness (Smith *et al.* 2004; Damasio 1999). Notably, visuals communicate impressions quickly and memorably, often in ways that are more accessible and persuasive than text (Barry 1997; Birdsell and Groarke 2007; Graber 1996; Blair 2012).

When compared to text, images are processed more quickly and contain a wealth of information (Graber 1996; Paivio 2013). Visual forms of communication are more memorable, especially when conveying novel or dramatic content, making them particularly influential on cognitive processes (Berry and Brosius 1991; Brosius 1991; Brosius, Donsbach, and Birk 1996; Edwards 2004). Audiences are also able to recall information from images more readily, particularly when these images contain dramatic or new information, enabling audiences to derive meaning more easily (Barthes 2015; Boehm 1995; Müller 2007; Fahmy, Bock, and Wanta 2014).

This influence is further accentuated in political contexts, where images can evoke strong emotions, shape attitudes, and act as significant drivers of public opinion (Coleman and Wu 2015; Hansen 2011; O’Neill *et al.* 2013; Banducci *et al.* 2008). When used strategically, images have the unique ability to bridge gaps between audiences and politicians, document events, and tap into societal symbols (Hariman and Lucaites 2007; Hill 2004; Perlmutter 2007). They can even introduce ambiguity into contentious messages (Blair 2012).

Visual communication extends beyond images to include nonverbal cues, such as facial expressions and gestures (Birdwhistell 2010; Argyle *et al.* 1970; Argyle, Alkema, and Gilmour 1971). These elements make up a significant portion of all communication and often take precedence over verbal messages, especially when the two are in conflict (Krauss *et al.* 1981; Noller 1985; Posner, Nissen, and Klein 1976). The integration of nonverbal cues with visual imagery illustrates the complexity and versatility of visual communication.

The ability of images to convey emotions, simplify intricate subjects, and transcend language barriers is multifaceted and powerful. Whether in political contexts, where they can shape public opinion and bridge gaps between audiences and politicians, or in the broader realm of human cognition, images play an indispensable role. Their impact is widely recognized in communication research (Zelizer 2010; Hokka and Nelimarkka 2020). Specifically, in the context of propaganda, images serve as compelling tools, shaping perceptions and beliefs; a subject that will be explored further in this study.

2.2 Images in Influence Operations

Images often used as a key persuasive tool in the context of infleunce operations. Here, an influence operation is defined as the tactical collection of information about an adversary coupled with the strategic dissemination of propaganda (RAND Corporation 2023).

The widespread adoption of social media has amplified the role of images in influence operations, allowing political actors to easily frame, filter, and manipulate visual content. The use of images as a tool for influence is particularly evident in populist leaders and far-right movements (Farkas *et al.* 2022; Wodak and Boukala 2015; Awad, Doerr, and Nissen 2022), and has also been embraced by extremist groups (Baele, Boyd, and Coan 2020). Within these extremist groups, hard propaganda imagery is used to exercise coercive strength through violence and weaponry, while soft propaganda highlights social aspects and cultural inclusivity within a group, portraying an appealing, normalized existence (Hashemi and Hall 2019). These forms of visual propaganda are strategically employed to idealize the mission of the extremist group and mobilize target audiences.

Among the various influence operations, those conducted by state actors toward international audiences on widely used platforms like Facebook and Twitter stand as the largest and most influential (Bradshaw, Bailey, and Howard 2021). The most prominent of these state actors are Russia, through the Internet Research Agency (IRA), and the People's Republic of China (PRC) (Bailey and Howard 2022).

The IRA exemplifies the strategic use of visual narratives in influence operations, portraying ordinary people and leveraging images to enhance emotional appeal (Bastos, Mercea, and Goveia 2023). This approach, marked by cultural sensitivity, often relies on familiar themes or images of relatable individuals to connect with targeted audiences. Such tactics seek to amplify discourse within specific subcultures, even going as far as impersonating groups like Black Lives Matter (Bastos and Farkas 2019; Freelon *et al.* 2022; Stewart *et al.* 2017). In contrast to traditional mass-produced propaganda, the IRA's activities demonstrate how images can be used alongside text to facilitate a nuanced engagement with particular subcultures or social identities (Jensen 2018; Kim *et al.* 2018; Linvill and Warren 2020; McGarty *et al.* 2014).

While Russia's influence operations are well-documented, other nation-states, such as the PRC, also engage in large-scale international influence campaigns. However, the PRC's use of visual communication in these efforts is less understood, a critical gap considering the growing importance of visual mediums in global politics.

2.3 China's International Influence Operations

In this study, I examine the use of images as a persuasive tool in the context of the CCP's international online influence efforts. The period for this study spans from 2011 to 2022, a time during which the CCP significantly expanded its online public diplomacy capacities and amassed a large international audience for its online messaging (Walker, Baxter, and Zamary 2021; Martin 2021; Chang 2021).

CCP-controlled media outlets have substantial followings on international social media platforms such as Facebook and Twitter (Olesen 2015; Tambe and Friedman 2022; The Economist 2019). Since these platforms are blocked within the PRC, they serve primarily as a channel for the CCP to reach and influence international audiences. The scale, funding, and reach of these campaigns signal their potential for wide impact, however, the motivations and objectives underpinning these efforts remain unclear.

Under Xi Jinping's leadership, the CCP's public diplomacy efforts have gained momentum. Xi's 2016 call for a "flagship media with strong international influence" (Central People's Government of the People's Republic of China 2016), coupled with the guiding principle "tell China stories well" (*jiang hao zhongguo gushi*) further reflects this focus (Xinhua 2013; Huang and Wang 2019; Tambe and Friedman 2022; Cook 2020). This commitment is also evident in the CCP's substantial public diplomacy investment. In 2020, the CCP's estimated annual expenditure on public diplomacy was around $8 billion, or four times that of the US (Walker, Baxter, and Zamary 2021; Martin 2021).

Part of this hefty investment has been directed toward expanding the CCP's global media reach through Party-controlled outlets. These include *China Daily*, *Xinhua News Agency*, *China Global Television Network (CGTN)*, *China Daily Group*, and *Global Times* (Brady 2009). In a notable example, *China Central Television*'s international arm underwent a rebranding to *CGTN* in 2016. Now broadcasting in five languages from three countries, this move has significantly extended its global reach (Reporters Without Borders 2019; Hamilton and Ohlberg 2020, p. 168). Adding to this media landscape, the *Global Times*, established in 2009, plays a distinct role by amplifying the Party's more assertive messages (Hamilton and Ohlberg 2020 p. 168). All these outlets are supervised by the State Council Information Office (Shambaugh 2007; Creemers 2015), and have successfully garnered substantial followings on international social media platforms. For instance, on Facebook, five CCP-controlled outlets are among the top fifty most 'liked' accounts (Social Blade 2023).

Here, I explore the strategic use of images by CCP-controlled media outlets on international social media platforms. The CCP has historically used imagery extensively in its messaging toward domestic audiences. A key example of this is its propaganda posters which in the past prominently featured: PRC leaders (Lago 1999); ethnic minorities (Li 2000); and women (Yin 2010). Propaganda posters provided visual information that was easily comprehensible, clearly outlining the behavior that was desired (Landsberger 2020), and the CCP used visual imagery in the these posters as a rhetorical tool to communicate its aspirational society to domestic audiences (King, Zheng, and Watson 2010).

Although the CCP no longer uses propaganda posters as its primary messaging tool, visual imagery is still an important means by which the PRC communicates with its domestic and international audiences. PRC state media, in particular, makes extensive use of images to accompany its articles. This study examine how images are used by the PRC as a framing tool in its international messaging.

3 Data

In an effort to explore how CCP-controlled media leverages images in international influence operations, this study builds on a dataset previously used by Bailey (n/d). This dataset is a comprehensive collection of Facebook posts created by internationally-focused CCP-controlled media outlets, spanning the years 2011 to 2022.

The starting point of 2011 was chosen by Bailey () due to the limited data on CCP-controlled media prior to this year, as the number of Facebook posts and audience engagements were insufficient to facilitate meaningful analysis. The dataset focuses on Facebook, a platform where CCP-controlled media have particularly large followings and is among the most popular social media platforms for internet users in predominantly English-speaking countries (YouGov 2022; Auxier and Anderson 2021).

The Facebook posts in this dataset are produced by prominent CCP-controlled media outlets that: (a) maintain an active Facebook presence; (b) target global audiences; (c) lack a specific subject area focus; and (d) primarily post in English. The media outlets that met these criteria as of January 2023 are: *China Xinhua News*; *CGTN*; *China Daily*; *Global Times*; *People's Daily*; *CCTV*; *Beijing Review*; and *China.org.cn*.

The text and metadata of these Facebook pages are extracted by Bailey () using the Facebook CrowdTangle API (CrowdTangle n.d.; Schliebs 2020). The dataset encompasses a total of 797,793 posts, receiving over 1.9 billion likes, 111 million shares, and 30 million comments during the period under investigation.

I build on the dataset used by Bailey () by scraping and analysing the images associated with these Facebook posts. Due to the CrowdTangle API limitations on bulk downloading, I was unable to retrieve the images contained directly within the posts. Instead, I created a scraper to extract the main images from the accompanying articles linked in the posts. The scraper used in this study is designed to target the primary image within each linked news article, or the largest image on the article page if no main feature image was HTML-coded.

Unfortunately, due to the age of many links, some were broken, and the scraper could not retrieve images where links did not lead to an active webpage. Out of 797,793 posts, 353,698 contained web links, and images were successfully scraped from 125,870 unbroken links. A manual inspection confirmed that these images were usually identical or highly similar to those used in the corresponding Facebook posts. Therefore, the dataset for this study consists of 125,870 images from links embedded in Facebook posts by CCP state-controlled media, in conjunction with the data from these Facebook posts.

4 Methods for Analysing Images

Analyzing images in large datasets requires a methodological approach that can strike a balance between scalability, interpretability, and adaptability. Various approaches have been explored in the literature, each with its own advantages and limitations. A frequently used method is qualitative, descriptive content analysis, involving manual coding of images (Aiello and Parry 2019; Russmann, Svensson, and Larsson 2019; Farkas *et al.* 2022; Farkas and Bene 2021). This approach involves a detailed human analysis of each image, allowing for the detection of symbols or elements with specific societal or cultural connotations. However, it is inherently limited by scale, rendering it unsuitable for a dataset exceeding 125,000 images, such as in this study. Additionally, the reliability of the coders can pose challenges.

Third-party object detection tools, such as those used in a study of candidate imagery during the 2019 European Parliamentary Election (Jungblut and Haim 2023), are suitable for detecting certain objects or features, like human facial expressions. However, akin to dictionary methods in text analysis, these tools are limited by what they have been trained to detect and lack adaptability or customizability to the images in each dataset.

Supervised approaches, as demonstrated by (Hashemi and Hall 2019), involve manual classification of a large number of images to train a machine learning model for specific tasks, such as real-time detection of visual propaganda. While this method allows for training a model to capture particular image symbols or elements, it is laborious and requires significant human effort to code the training data.

The approach presented in this article employs unsupervised machine learning to detect the hidden thematic structure in large collections of images. Unlike the methods mentioned above, this approach requires no manual coding, making it scalable to any number of images. It is conceptually similar to topic modeling in text analysis, where themes are detected within a dataset.

This novel method offers a scalable and adaptable solution, particularly well-suited for large and diverse image datasets.

4.1 Unsupervised Learning for Image Classification

In this article, I propose a two-step approach to unsupervised image classification. First, I train an image embedding model to transform raw image data into numerical vectors. Second, following the transformation, I use a k-means clustering approach to identify and measure prevalent image elements within the data.

The concept of embeddings, widely recognized in text analysis, serves as the foundation for this approach. Language representation models transform text meanings into numerical representations, capturing semantic and syntactic relationships among words (Pennington, Socher, and Manning 2014; Bengio *et al.* 2003). These dense, real-value vectors, or word embeddings, predict a word's likelihood based on its context and allow for the measurement of word or phrase similarity within the corpus context (Collobert and Weston 2008; Mikolov *et al.* 2013). The underlying principle aligns with the distributional hypothesis, asserting that a word's meaning can be inferred from its context (Firth 1957, p. 11). Political scientists and social scientists have used word embeddings to capture and quantify latent concepts, track changes in ideology, and detect specific sentiments (Rheault and Cochrane 2020; Rodman 2020; Kozlowski, Taddy, and Evans 2019; Rice and Zorn 2021). This method has proven effective in revealing subtle and complex relationships within textual data.

Building on this foundational understanding of word embeddings, I adapt the technique to analyze images. Rather than embedding text, I focus on embedding images, capturing their semantic meanings. This approach leverages the principle that images containing similar content tend to have similar embeddings, a property that is particularly important for tasks like image similarity search and clustering. By embedding the images, this method offers a scalable and insightful way to explore the visual data, echoing the successes found in text analysis. The integration of k-means clustering further enhances the ability to signpost particularly prevalent image elements and measure the similarity of each image to those elements.

Before training the model, each image is cropped to a uniform size suitable for image embedding. The EfficientNet model is then used to embed the images. EfficientNet is selected for its ability to balance the tradeoff between the number of parameters and accuracy, facilitating faster training and inference without sacrificing performance (Tan and Le 2019). For this particular dataset, the optimal configuration is achieved with 126 shards, each containing 1000 images.

After embedding the images, I inspect a random selection of k-nearest neighbors within the model to validate the embedding of visual similarity. The concept of nearest neighbors is grounded in the notion of cosine similarity, a measure that quantifies the cosine of the angle between two vectors in a multi-dimensional space. Cosine similarity is expressed mathematically as,

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{||\mathbf{A}|| \times ||\mathbf{B}||} \tag{1}$$

where **A** and **B** are the vectors being compared, and $\cos(\theta)$ is the angle between them. This inspection of k-nearest neighbors affirms that the model effectively embeds visual similarity, as the images that are nearest neighbors in the embedding space are visually highly congruent.

Figure 1 illustrates this alignment. At the top of the figure is a randomly selected image from the dataset, depicting produce at a market. Below this image are the ten most similar images in terms of k-nearest neighbor embeddings, all of which portray semantically consistent scenes of market produce. This similarity between images and their nearest neighbors is a pattern replicated across the dataset, confirming the model's ability to capture and quantify visual resemblance.

Figure 1. An Illustration of Visual Similarity through k-Nearest Neighbors in Image Embedding Space

4.2 K-Means Signposting the Embedding Space

Following the validation of visual similarity through k-nearest neighbors, this method explores thematic clusters within the image embeddings. This stage uses k-means clustering to partition the embeddings into 100 clusters. The purpose of this clustering is not to actively group the images, but rather to signpost areas of high concentration in the embedding space, thereby providing some structure to the dataset. I use this approach to identify large clusters in the embedding space that can serve as key signposts, highlighting prevalent themes or visual elements within the dataset.

Each image is represented as a numerical vector x in the embedding space. The clustering is performed using the k-means algorithm, defined by the objective function

$$\min \sum_{k=1}^{K} \sum_{\mathbf{x} \in C_k} \|\mathbf{x} - \mathbf{m}_k\|^2, \tag{2}$$

where K is the number of clusters, C_k is the set of points in cluster k, and $\mathbf{m}_k$ is the centroid of cluster k, given by

$$\mathbf{m}_k = \frac{1}{|C_k|} \sum_{\mathbf{x} \in C_k} \mathbf{x}. \tag{3}$$

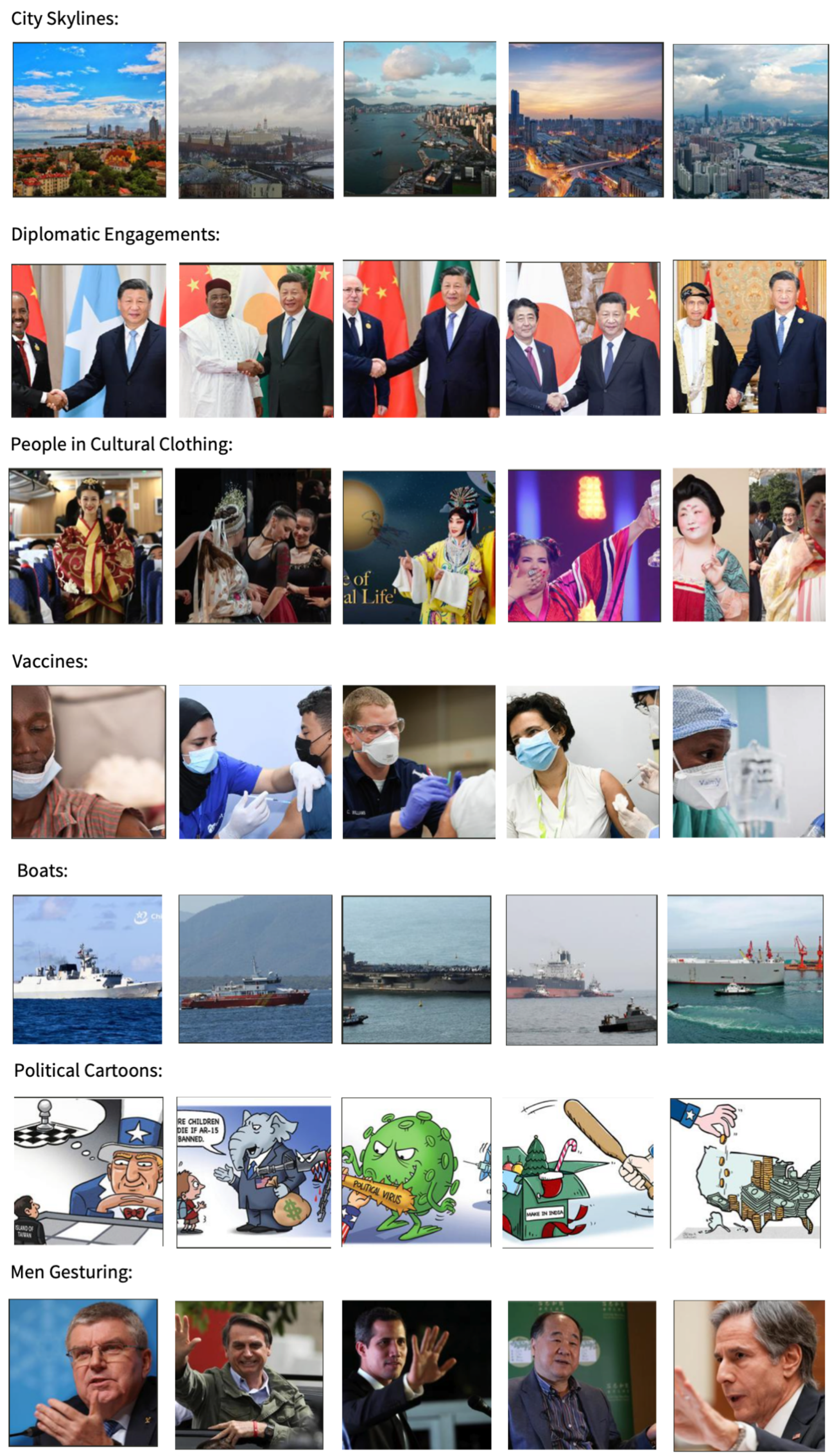
For the given dataset, $K = 100$, and clusters with sizes above a certain threshold are considered large clusters. The threshold is defined as a specific percentile of the cluster sizes.

I calculate the centroids of the image vectors within these large clusters, representing central thematic points. Using the 10 k-nearest neighbor images closest to each centroid, I manually label these centroids with descriptive names such as 'Political Leaders at Podiums,' 'COVID Healthcare Workers,' and 'Industrial Machinery'.

Next, I compute the cosine similarity between the 125,870 image embeddings and the identified centroids. This results in a similarity score for every image, normalised to range from near 0 (not similar) to near 1 (very similar). This method allows a nuanced mapping of how each image relates to the thematic clusters, similar to assigning topic scores in text analysis.

Figure 2 provides illustrative examples of images within the dataset that are nearest neighbors to the large clusters identified. These images were used to assign manual labeling of each cluster signpost. The selected examples in Figure 2 represent a diverse range of visual phenomena, from 'City Skylines' to 'Political Cartoons.' This variety underscores the model's capability to encode similarities across different visual themes.

Figure 2. Illustration of Nearest Neighbor Images to Large K-Means Clusters



To illustrate the relationship between cluster centroid signposts and the underlying structure of the image embedding space, I use a t-Distributed Stochastic Neighbor Embedding (t-SNE) plot. t-SNE is a widely-used dimensionality reduction technique that visualizes high-dimensional data in a lower-dimensional space, typically two or three dimensions. By preserving the local structure of the data, t-SNE allows for the identification of patterns and clusters in the original high-dimensional space.

Figure 3. t-SNE Visualization of Image Embeddings and Cluster Centroid Signposts

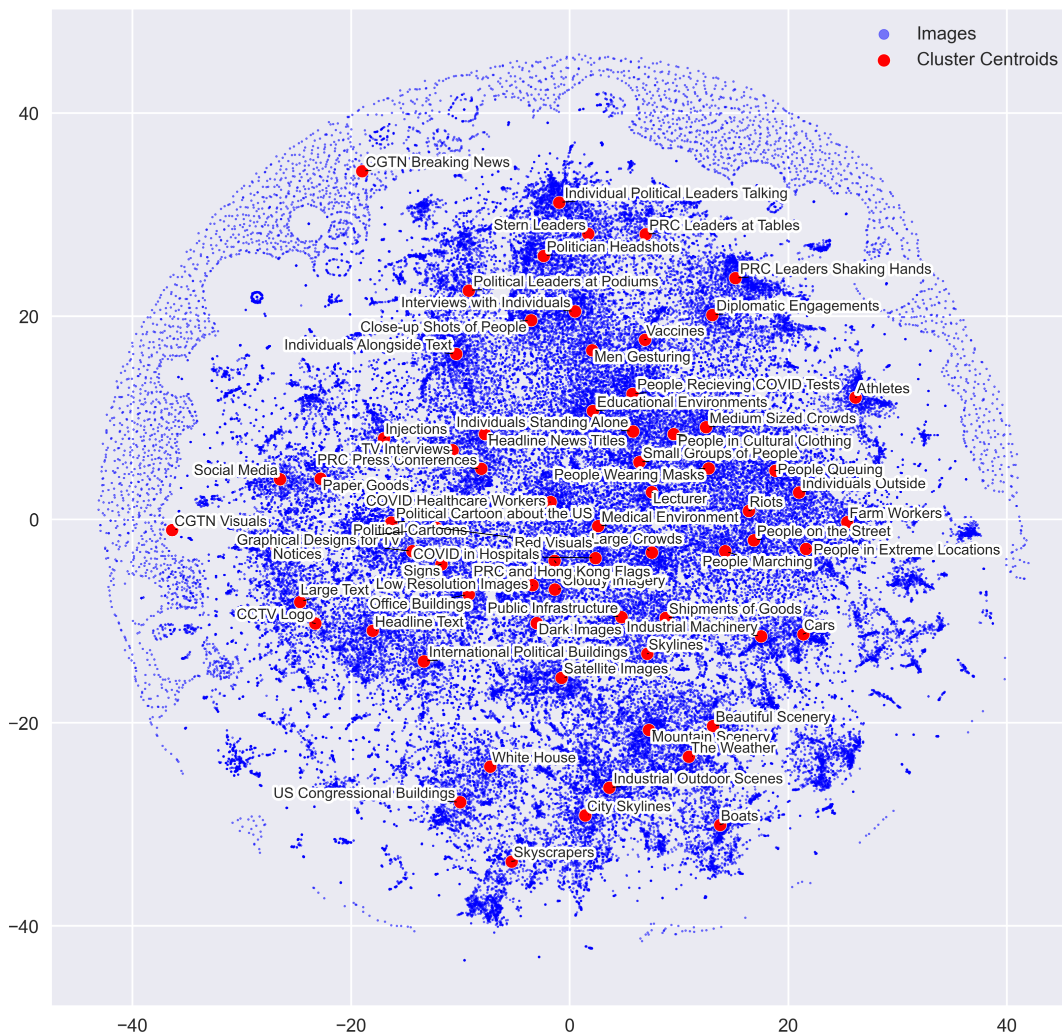
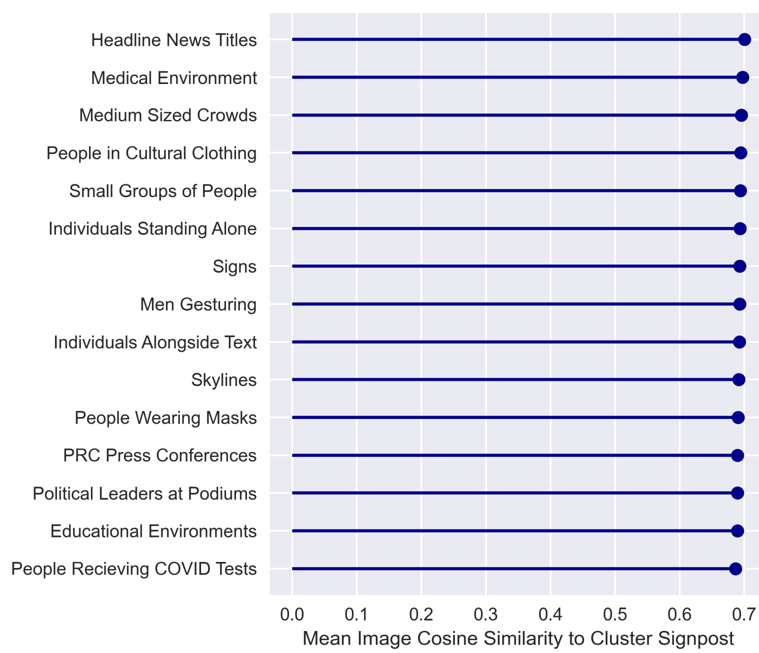


Figure 3 provides a visualization of the image embeddings generated by the model, alongside the identified signposts, within the t-SNE plot. This illustration reveals the positionality of the signposts within the embedding space, demonstrating that signposts referring to similar concepts are located in proximate areas. For example, images representing political leaders are clustered in the top section, groups of people are found in the right-hand corner of the plot, and buildings and scenery are grouped below the midpoint of the t-SNE plot. This spatial arrangement provides further evidence that the model effectively encodes visual similarity; images with semantically similar content yield similar embedding vectors, while images with dissimilar content diverge.

The patterns observed in Figure 3 underscore the model's capability to capture and quantify complex visual relationships, providing further evidence of the effectiveness of the k-means clustering and image embedding approach. However, it is important to recognize the limitations inherent to t-SNE visualization. The algorithm's stochastic nature may produce varying visualizations in different runs, and its sensitivity to hyperparameters like perplexity and learning rate can influence the resulting plot. Therefore, while Figure 3 serves as an overall impression rather than a definitive representation of the dataset's structure, it does highlight the method's value in quantifying thematic clusters and exploring large and diverse image datasets through unsupervised learning.

In further quantifying the relationship between images and cluster signposts, I use cosine similarity measures, as previously detailed, to calculate the image similarity relative to each signpost. Figure 4 highlights the fifteen signpost clusters with the highest mean image cosine similarity within the dataset of CCP-controlled articles posted on Facebook, offering insights into the dominant visual themes.

Figure 4. Visualization of the Fifteen Signpost Clusters with the Highest Mean Image Cosine Similarity



These clusters encompass a diverse array of visual components, including expected media elements such as headlines, signs and accompanying text. Notably, a recurrent theme emerges in the form of varying-sized crowds or groups of people. Political imagery, represented by clusters such as 'PRC Press Conferences', 'Political Leaders at Podiums,' and 'Men Gesturing', a cluster featuring male leaders gesturing toward the camera, is also prominent. There are three potential

COVID-related clusters, ‘People Wearing Masks’, ‘People Receiving COVID Tests’ and ‘Medical Environment’.

5 Results

6 Discussion and Conclusion

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