

# Pictures as a Form of Protest: A Survey and Analysis of Images Posted During the Stop Asian Hate Movement on Twitter

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**Abstract**—Modern protests are not limited to on-the-ground operations, and the ease and speed at which users can upload images to social media platforms has enabled protests to manifest online. Previous analysis of protest imagery from social media sites categorized these images into groups including texts, screenshots, memes, and artwork. However, large-scale manual annotation to identify different types of images is not feasible. By applying machine learning to a large Twitter dataset focused on the Stop Asian Hate movement, we found the type of image an account posted during protests on Twitter is tied to the credibility and political leaning of posted content, type of witnessing (remote or connective), and community formation.

**Index Terms**—images, protest, social media, social movements, Twitter, visual analysis, machine learning

## I. INTRODUCTION

Social media platforms such as Twitter have enabled users to participate in protests by simply uploading images. Photographs have become a form of visual protest through this “connective witnessing” [1], where individuals contribute to the flow of information by sharing eyewitness photographs of an event. Researchers have also observed the phenomenon of “remote witnessing” [2] where accounts appropriate secondary sources, e.g. posting screenshots of news articles.

Previous work focuses on small samples of popular or commonly re-posted images understood through manual annotation [2], [3], but there is little research on how these different types of images exist across an entire movement due to the sheer volume of images involved. In order to bridge this gap, we ask the following questions: 1) how can we apply machine learning techniques to identify and classify types of protest imagery on Twitter and 2) how do accounts leverage images to participate in protest discourse on social media?

## II. METHOD

We extended previous work by developing a method to classify images by type in a large Twitter dataset using the convolutional neural network ResNet50 [4]. We then applied this method to the recent Stop Asian Hate movement to

better understand how different types of images contributed to political- and misinformation-related discourse.

We used a dataset focused on the Stop Asian Hate movement, which appeared in response to the rise of anti-asian hate crimes in the wake of the Covid-19 pandemic. We started with a dataset of 4.2 million tweets and selected a subset of accounts who posted at least one domain and at least one image. Images posted by these accounts were classified into one of 7 categories (infographics, photographs with graphics or text, photographs, illustrations with text, illustrations, texts, and screenshots). We also collected the number of right-leaning, left-leaning, low-credibility and high-credibility domains<sup>1</sup> that each account posted and built a retweet network where each account was labelled with the type of image that it retweeted the most.

## III. RESULTS

### A. Network Structure

In the over 1.3 million images that were analyzed approximately 50% of the images shared were photographs, which supports Jenzen et. al.’s findings [3]. Infographics made up approximately 25% of the corpus, and screenshots and texts each made up about 12% of the corpus.

As seen in Fig. 1, the core of the network (E) is split into two halves: on the left, accounts shared mostly photographs while on the right, accounts shared mostly infographics. Smaller communities formed outside of the cluster E. For example, cluster A is a tightly knit community of accounts that mostly shared screenshots, cluster B shared mostly photographs, while clusters C and D shared primarily infographics. These clusters indicate that accounts who posted protest-related images on social media interacted with accounts who participated in a similar way.

### B. Images and Protest Discourse

Overall, we found that the types of images that an account shared were tied to the political lean and credibility of

The authors gratefully acknowledge support from the National Science Foundation Research Experiences for Undergraduates grant #2051101.

<sup>1</sup>Ratings for credibility and political leaning of domains were taken from Media Bias/Fact Check (<https://mediabiasfactcheck.com/>)

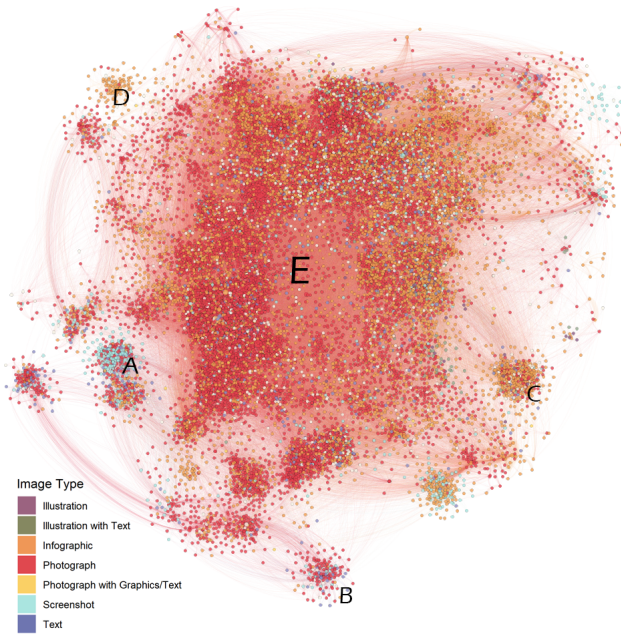


Fig. 1. Retweet network of the most active accounts where nodes represent accounts and edges go from retweeted account to retweeting account. Nodes are sized according to out-degree.

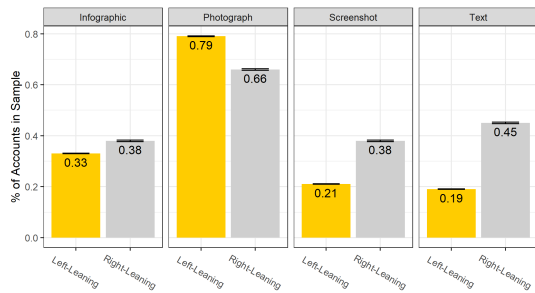


Fig. 2. The percentage of accounts that tweeted at least one of the labelled image type (e.g. screenshot, infographic), given that the account had also tweeted at least one left- or right-leaning domain. Standard error bars included.

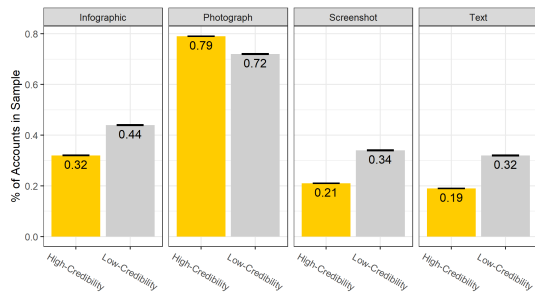


Fig. 3. The percentage of accounts that tweeted at least one of the labelled image type (e.g. screenshot, infographic), given that the account had also tweeted at least one high- or low-credibility domain. Standard error bars included.

content they posted, as well as their propensity for remote or connective witnessing. As seen in Figure 2, accounts that shared right-leaning domains were more likely to share texts and screenshots and less likely to share photographs than their left-leaning counterparts. This suggests that right-leaning accounts tended to use text-based mediums associated with remote witnessing, and left-leaning accounts tended to share more photographs, which are associated with connective witnessing. Similarly, Figure 3 shows that accounts who shared low-credibility domains were more likely to share texts and screenshots and less likely to share photographs than their high-credibility counterparts. This suggests that low-credibility accounts also tended to engage more in remote witnessing, and high-credibility accounts tended towards connective witnessing.

Infographics stood out because they made up a significant portion of our corpus but did not fall neatly into either remote or connective witnessing. However, infographics still played an interesting part in protest discourse. As seen in Figure 2, right-leaning accounts were more likely to share texts than infographics, and Figure 3 shows low-credibility accounts were more likely to share infographics over texts. This difference in how infographics, which we define as text with graphic elements added, and how plain text images were shared suggests design elements may have played a role in how these types of images were utilized in protest discourse.

#### IV. CONCLUSION AND FUTURE DIRECTIONS

This investigation into protest imagery posted during the Stop Asian Hate movement on Twitter revealed that image type was tied to credibility, political lean, type of witnessing (connective or remote), and community formation. Future research directions include investigating the prevalence of infographics, which made up a quarter of our corpus but did not fall into connective or remote witnessing, as well as text-based images in general, which were popular in our dataset despite the fact that Twitter already provides a space to post text within the body of a tweet. A more in-depth look at text-based images and their aesthetics and composition will enable us to determine if accounts share certain images based on content or visual appearance, and how image design might be leveraged by bad actors to spread disingenuous content.

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