

ImageArg: A Multi-modal Tweet Dataset for Image Persuasiveness Mining

Anonymous Argument Mining Workshop submission

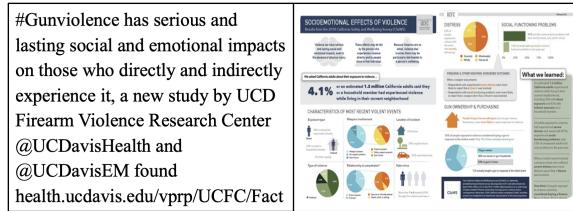
Abstract

The growing interest in developing corpora of persuasive texts has promoted applications in automated systems, e.g., debating and essay scoring systems; however, there is little prior work mining image persuasiveness from an argumentative perspective. For expanding persuasiveness mining to a multi-modal realm, we present a multi-modal dataset, *ImageArg*, consisting of annotations of image persuasiveness in tweets. The annotations are based on a persuasion taxonomy that we developed to explore image functionalities and the means of persuasion. We benchmark image persuasiveness tasks on *ImageArg* using widely-used multi-modal learning methods. The experimental results show that our dataset offers a useful resource for this rich and challenging topic, and there is ample room for modeling improvement.

1 Introduction

Argumentation mining (AM) aims to analyze authors' argumentative stance by automatically identifying argumentative structures and their relationships (Green et al., 2014). As a fundamental component in AM, computational persuasiveness analysis has gained considerable momentum due to growing resources and downstream applications (Chatterjee and Agrawal, 2006; Park et al., 2014; Wei et al., 2016; Lukin et al., 2017; Chakrabarty et al., 2017; Lytos et al., 2019). Aiming at automatically evaluating how well one party can change another party's opinions or behaviors, computational persuasiveness tasks are critical yet challenging.

Recent work in AM has brought attention to mining persuasiveness in essays. Stab and Gurevych (2014) and Habernal and Gurevych (2017) developed the Argument Annotated Essays Corpus (AAEC) where stance, argument components, and argumentative relations were annotated. Carlile



(a) A posted tweet text

(b) An associated posted tweet image

Figure 1: (a) The tweet text uses gun violence to argue for *gun control*. (b) The image makes the argument more persuasive by providing supplementary statistics relating violence to gun ownership in California.

et al. (2018) extended AAEC annotations with persuasiveness scores, as well as with argumentative attributes that potentially impact persuasiveness (Eloquence, Specificity, Relevance, and Evidence) and the means of persuasion (Ethos, Pathos, or Logos). These are all text-based; however, missing the opportunity to leverage other modalities (e.g., images) that potentially enhance the persuasiveness of the argument. For example, the image showing statistic charts in Figure 1 makes the tweet text more convincing. To address the gap that image persuasiveness has rarely been explored in the AM community, we create a new multi-modal dataset, *ImageArg*¹, that annotates image persuasiveness in tweets and extends persuasiveness mining to a multi-modal realm.

Regarding *ImageArg* construction, we first extend annotation schemes that are previously developed to capture the persuasive strength of text arguments in AAEC (Duthie et al., 2016; Wachsmuth et al., 2018; Carlile et al., 2018) to a new modality of image. Specifically, we develop a novel strategy (Sec. 3.2) to annotate multi-modal persuasiveness gains that measure if the persuasiveness of a tweet's text increases after adding a visual image. Second, we devise a taxonomy to annotate image content

¹The dataset will be released upon paper publication.

(Sec. 3.3) that explicitly identifies image functionalities from a persuasive perspective. Furthermore, we adapt existing text attributes used in Carlile et al. (2018) to annotate image persuasion modes (Sec 3.4) by exploring different annotation strategies (Sec 4.2). We evaluate the inter-rater agreement on our proposed annotation schemes as well as the quality of the annotated samples.

With *ImageArg*, we first report the basic statistics of the dataset and conduct a thorough analysis between different annotation dimensions (Sec 4.3). We observe a strong correlation between human political ideology (i.e. stance towards a social topic) and the argumentative features in their posted tweets, as well as mutual influences between image content and persuasion mode. In addition, we benchmark model performance on multiple argumentative classification tasks annotated in *ImageArg* (Sec 5.2). Specifically, we employ multi-modal learning methods to classify stance, image persuasiveness, image content, and image persuasion mode. Our benchmark results highlight the challenge of these tasks and indicate there is ample room for model improvement. We demonstrate the limitation of these general multi-modal methods and discuss possible future work. We further conduct a qualitative study on a real-world application, retrieving the most persuasive images given a tweet text, by using our trained classifiers (Sec 5.3), which offers a starting point for developing an intelligent tool that recommends persuasive images to users based on their textual inputs.

2 Related Work

Computational Persuasiveness While classical AM focuses on identifying argumentative components and their relations (Stab et al., 2014, 2018; Lawrence and Reed, 2020), recent work has developed interest in persuasiveness related tasks (Chatterjee et al., 2014; Park et al., 2014; Lukin et al., 2017; Carlile et al., 2018; Chakrabarty et al., 2020). In addition, Riley (1954), O’keefe (2015), and Wei et al. (2016) investigate ranking debate arguments on the same topic based on their persuasiveness, but they failed to investigate the factors that make arguments persuasive. Lukin et al. (2017) and Persing and Ng (2017) examine how audience variables (e.g., personality) influence persuasiveness through different argument styles (e.g., factual vs. emotional arguments), but only focus on the text modality. Higgins and Walker (2012) and Carlile et al.

(2018) study the persuasion strategies, i.e., ethos (credibility), logos (reason), and pathos (emotion), in the scope of reports or student essays. We follow their work developed for text corpora and extend the annotation schemes to the image modality. Although Park et al. (2014), Joo et al. (2014), and Huang and Kovashka (2016) utilize facial expressions and bodily gestures to analyze persuasiveness in social multimedia, their work is limited to the human portrait and fails to generalize to diverse image domains. Some prior work study persuasive advertisements in a multi-modal way (Hussain et al., 2017; Guo et al., 2021). Different from our argumentative mining goal, they focus on the sentiment, intent reasoning and persuasive strategies that are narrowly designed for ads. Thus, annotating a multi-modal tweet dataset focusing on image persuasiveness is under-explored in existing work, and has ample value for social science.

Multi-modal Learning The ability to process and understand multi-modal input for AI models has recently received much attention since the multi-modal signals are generally complementary for real-world applications (Aytar et al., 2016; Zhang et al., 2018; Alwassel et al., 2020). In the area of vision-language, tasks are mainly designed for evaluating models’ ability to understand visual information as well as expressing the reasoning in language (Antol et al., 2015; Goyal et al., 2017; Hudson and Manning, 2019). In addition to the main stream, a few works study the relationship between image and text: Alikhani et al. (2019) annotates the discourse relations between text and accompanying imagery in recipe instructions; and Kruk et al. (2019) investigates the multi-modal document intent in instagram posts. However, multi-modal learning for AM has been under-explored due to a lack of multi-modal corpora. This drives us to build *ImageArg* and to analyze the effectiveness of multi-modal learning on AM tasks. With respect to modeling, researchers focus on learning good representation of each modality and developing effective fusion methods (Tsai et al., 2018; Hu et al., 2019; Lu et al., 2020; Tan and Bansal, 2019). In this work, we establish a benchmark performance for *ImageArg* by using fundamental and common encoders and fusion methods.

3 Annotation Scheme

We propose an annotation scheme to capture an image’s impact on the persuasiveness of multi-modal

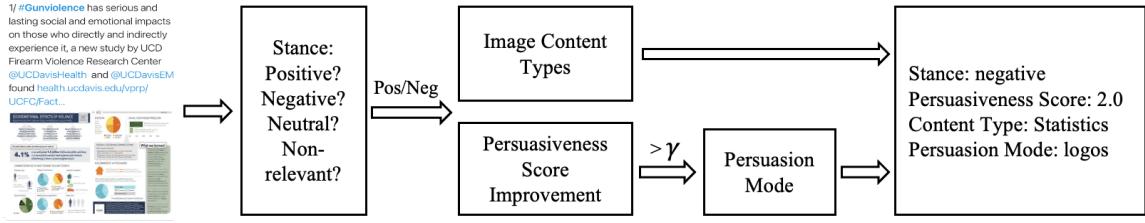


Figure 2: The overview of our annotation pipeline. Annotators start by annotating the argumentative stance of input tweets. Afterwards, tweets with either positive or negative stances are annotated for image content types and persuasiveness score improvement. The persuasion mode is further annotated if persuasiveness score improvement exceeds a given threshold γ . We use $\gamma = 0.5$ when annotating data but test with different γ values for persuasiveness classification task (Table 5).



Figure 3: Examples of positive (support) and negative (oppose) tweets.

tweets. We build a corpus of Twitter posts on a social topic (e.g., *gun control*), then annotate the image within each post along four dimensions. The annotation pipeline is shown in Figure 2. First, we determine (1) the **stance** of the entire tweet (Sec. 3.1). Specifically, we assume one tweet holds a consistent stance in its text and image since the author would intend to deliver a consistent argument. For those tweets annotated with a positive or negative stance, we also annotate (2) the **persuasiveness scores** of the tweet image (Sec. 3.2) and (3) the image **content type**. The content types identify image roles from an argumentative perspective (Sec. 3.3). Finally, we (4) identify the **persuasion mode** of an image that is annotated as persuasive. The persuasion mode indicates how the images persuade audiences (Sec. 3.4). Note that with this annotation pipeline, all tweets will first be annotated for stance. Then, only tweets with a clear stance will be annotated for content type and persuasiveness scores. Finally, only tweets where the images are persuasive will be annotated for persuasion mode.

3.1 Stance

We use existing methods (Mohammad et al., 2017) to verify if the image holds a clear stance on a given topic. Specifically, given a tweet (including text and images), we ask annotators to select among

four stances that are extended from Mohammad et al. (2017): positive (i.e., support), negative (i.e., oppose), neutral, or irrelevant to the topic. We continue with the next annotation steps only if a tweet holds a positive or negative stance. Otherwise, it is discarded for our persuasion study. We show examples in Figure 3.

3.2 Image Persuasiveness Scores

For a tweet that holds a positive or negative stance, we study the impact of its image by computing an image persuasiveness score improvement. We adopt five levels of text persuasiveness scores proposed in Carlile et al. (2018) in the annotation process: (L0) no persuasiveness (score = 0): the annotated target fails to convince the audience at all. (L1) medium persuasiveness (score = 1): the annotated target partially convinces the audience. (L2) persuasive (score = 2): the annotated target is convincing to the audience. (L3) high persuasiveness (score = 3): the annotated target is very convincing to the audience. (L4) extreme persuasiveness (score = 4): the annotated target is compelling to the audience.

Different from Carlile et al. (2018) that annotates the persuasiveness score directly, we propose a novel method to compute the image persuasiveness score. In particular, we calculate the differences with/without images to quantify image persuasiveness scores. We first ask annotators to choose one of 5 persuasiveness levels based on pure text from the tweet. Next, we ask annotators to give a second choice based on both text and image from the tweet. Suppose each sample has five annotations and each annotation has two persuasiveness scores: one for the text-only (s_t), the second one for the image-text (s_{it}). We compute the persuasiveness score of image $\Delta s_i = \max(s_{it} - s_t, 0)$ for each annotation, as the improvement from the image. Then, we compute the average of the five annotations as the final

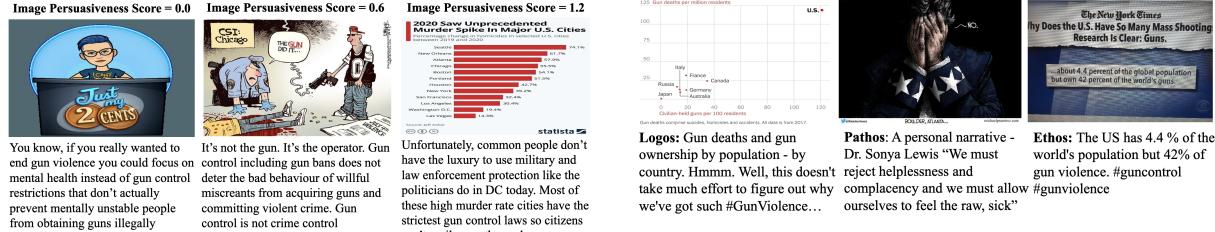


Figure 4: Examples of tweets with 0, 0.6, and 1.2 image persuasiveness scores.

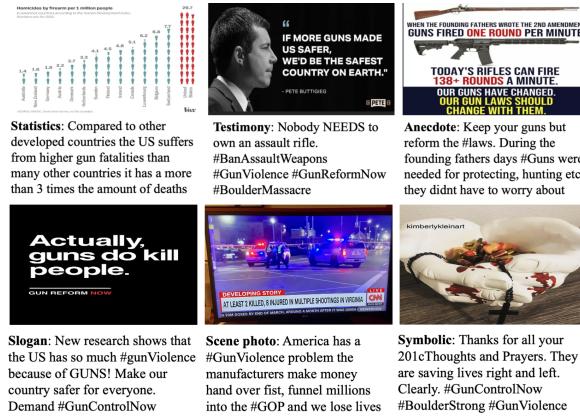


Figure 5: Examples of image content types in tweets: statistics, testimony, anecdote, slogan, scene photo, and symbolic.

image persuasiveness score. We use a threshold (γ) to filter the persuasive images. If Δs_i is higher than the threshold, it indicates that adding images improves the persuasiveness, then the images are considered as persuasive. We show examples of tweets with different image persuasiveness scores in Figure 4.

3.3 Image Content Types

For persuasive samples, we investigate their image argumentative roles. In particular, we annotate the image content types from an argumentative perspective to describe what kind of evidence images provide to improve tweet persuasiveness (e.g., supportive data, authorized photos, etc.). We leverage Al Khatib et al. (2016)'s definition of argumentative roles of evidence to categorize image content: Statistics, Testimony, and Anecdote. However, we notice that the categories fail to capture all the image contents that frequently appear in tweet posts, for example, photographs. To this end, we propose a Slogan category highlighting text in images, and also propose Scene photo and Symbolic photo categories regarding image content in the visual modality. More details are specified as follow,



Figure 6: Examples of persuasion mode in tweet: logos, pathos, and ethos.

- **Statistics:** Images provide evidence by stating or quoting quantitative information, such as a chart or diagram showing data, that is related to the tweet text. In Fig. 5, the image provides quantitative statistics on gun fatalities.
- **Testimony:** Images quote statements or conclusions from an authority, such as a piece of articles or claims from an official document, that is related to the tweet text. For example, in Fig. 5, the testimony image cites a statement given by the transportation secretary.
- **Anecdote:** Images provide information based on the author's personal experience, such as facts/personal stories, that are related to the tweet text. In Fig 5, the anecdote image shows the fact that guns are developed since the period of the 2nd amendment, and therefore the laws for guns should be developed as well.
- **Slogan:** Images embed pieces of advertising/slogan text. In Fig. 5, the slogan image presents a phrase "Actually guns do kill people. Gun Reform Now".
- **Scene photo:** Images show a real scene or photograph that is related to the tweet text. In Fig. 5, the image shows a photo of a gun violence scene reported by CNN news.
- **Symbolic photo:** Images show a symbol/art that expresses the author's viewpoints in a non-literal way. In Fig. 5, the symbolic photo shows a pair of artificial bloodied hands holding bullets and a cross which symbolically reveals the brutality of gun violence.

3.4 Image Persuasion Modes

To investigate how images convince an audience (e.g., by providing strong logic, touching audiences emotionally, etc.), we annotate the persuasion modes of images by leveraging the definitions in Braet (1992) for Logos, Pathos, and Ethos. The modes form the rhetorical triangle, and both the textual and visual modalities follow these dimensions

Task	Alpha	Count
Stance	64.5	87
Content type	71.1	38
Persuasion mode	19.9	38

Table 1: First pilot annotation inter-agreement on *gun control* topic. Persuasion modes are annotated as single choices from logos, pathos, and ethos.

in the persuasiveness perspective. Fig. 6 shows examples, details are specified below:

- **Logos:** The image appeals to logic and reasoning, which persuades audiences with reasoning from a fact/statistics/study case/scientific evidence. In Fig. 6, the Logos image provides a chart that shows the high gun deaths and the high gun ownership by the population of the US, which implies a logical relationship between gun death and gun ownership.
- **Pathos:** The image appeals to emotion, i.e., evokes emotional impact that leads to higher persuasiveness. In Fig. 6, the Pathos image provides art that shows the grieved "Uncle Sam" saying "no" with helplessness, which evokes the desire to *gun control*.
- **Ethos:** The image appeals to ethics, which enhances credibility and trustworthiness. In Fig. 6, the Ethos image takes a screenshot of the source of a report from New York Times, which increases credibility.

4 Corpus Creation

4.1 Data Collection

We collect raw tweets containing both image and text across 3 topics (*gun control*, *immigration* and *abortion*) used in [Mochales and Moens \(2011\)](#) and [Stab et al. \(2018\)](#). Specifically, we retrieve tweets with images that contain pre-defined keywords² through TwitterAPI³. The raw data are collected from March 29, 2019 to March 29, 2021. We retain tweets whose text content tends to be argumentative (with an argument confidence score larger than 0.9) by using ArgumentText Classify API⁴. This procedure ensures the corpus has high argumentation-confidence and topic-relevance.

4.2 Annotation Strategies

We developed annotation strategies based on several rounds of pilot annotations. To ensure the

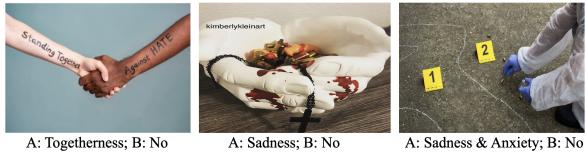


Figure 7: Annotator A annotates as pathos as these examples express emotions, while annotator B disagrees and marks as not pathos.

Task	Alpha	Count
Stance	76.1	1003
Persuasiveness*	/	1003
Content type	64.6	1003
Logos	55.3	259
Pathos	51.0	259
Ethos	57.8	259

Table 2: Inter-agreement rate of each annotation task in our final corpus on *gun control* topic, and the number of samples with the corresponding annotation. (*) We only show numbers of persuasiveness since they are annotated with average persuasiveness scores from annotators rather than labels.

annotation quality, we provide coding manual and examples for annotators (see the Appendix B for details). We employ qualified workers who passed a qualitative test that evaluates the workers' understanding on our annotation manual. In the first-round, we distributed 87 samples on the *gun control topic* to two random annotators on MTurk. Table 1 shows Krippendorff's alpha ([Krippendorff, 2011](#)) score for inter-rater agreement⁵. Based on the interpretation of alpha scores in [Hartling et al. \(2012\)](#); [Landis and Koch \(1977\)](#), we conclude that stance and content type have a substantial inter-agreement but persuasion mode inter-agreement is slight. To investigate this issue, we modified our annotation guideline for persuasion mode. Instead of using three-class annotation, we move to three-label annotation that allows multiple labels for each sample. Specifically, the annotator is asked to decide whether the image appeals to each persuasion mode separately (i.e., annotating yes/no for each mode). Moreover, the annotator is requested to justify their choice in a short sentence. The improved results are shown in Table 2, although the persuasion mode agreement (i.e., logos, pathos, and ethos) is still less than stance and content type. This is likely because annotators have different emotional reasoning (i.e., some annotators are easily evoked by

²We use keywords provided in [Guo et al. \(2020\)](#)'s work.

³<https://developer.twitter.com/en/docs/twitter-api>

⁴<https://api.argumentsearch.com>

⁵Note that the availability of annotation questions is based on the answer to the prior questions (Figure 2) therefore each task has different sample numbers.

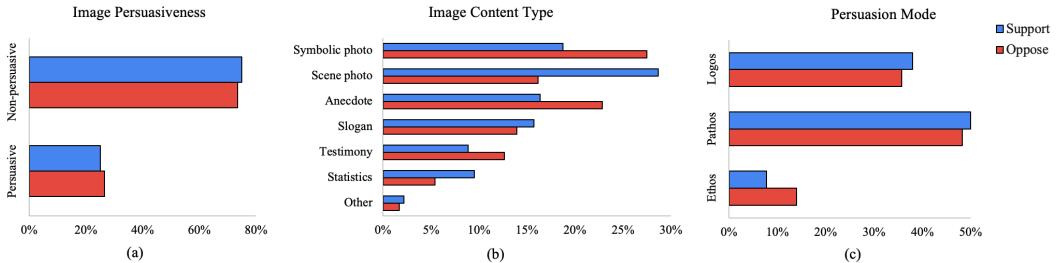


Figure 8: Distributions of (a) image persuasiveness, (b) content type and (c) persuasion mode regarding stances in our corpus on *gun control* topic.

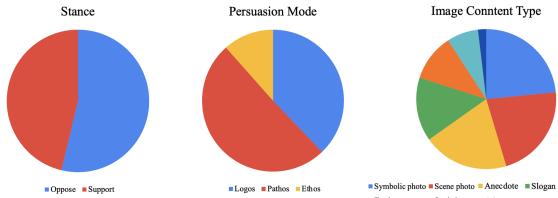


Figure 9: Distributions of stance, persuasion mode, and image content types.

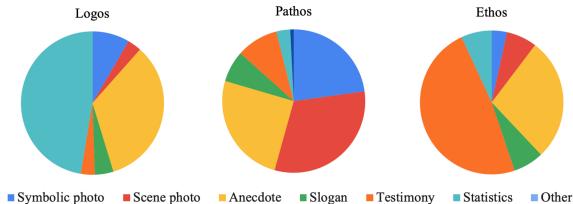


Figure 10: Distributions of image content types in different persuasion mode samples in our corpus on *gun control* topic.

images while others are not). As shown in Figure 7, one annotator recognized strong emotional impact (e.g., togetherness, sadness, anxiety, etc.), while the other not.

After annotating *gun control*, we also perform pilot annotations for the *immigration* and *abortion* topics. These receive substantial/moderate agreement on stance and content type but pathos is only fair (details are described in Appendix A). These studies show that the inter-rater agreement on annotating persuasion mode is topic-dependent. We thus create the first version of *ImageArg* data using only the *gun control* topic, and leave the other two topics for future work.

4.3 Corpus Statistics and Analysis

We annotate 1003 samples that hold a stance on *gun control* topic. The distribution of each annotation scheme is shown in Figure 9. We show the inter-rater agreement metrics in Table 2. The results show that the annotators have substantial

Persuasiveness Score	Count	Percentage
0.0 - 0.2	336	33.50%
0.2 - 0.4	232	23.13%
0.4 - 0.6	176	17.55%
0.6 - 0.8	118	11.76%
0.8 - 1.0	66	6.58%
≥ 1.0	75	7.48%

Table 3: The annotated image persuasiveness scores distribution on *gun control* topic in *ImageArg*.

agreement on the stance and content types and moderate agreement on the persuasion mode of the image. In our *gun control* corpus, the stances are balanced (46.3% positive and 54.7% negative). Table 3 shows the sample distribution of image persuasiveness score in different intervals. We set the threshold γ equal to 0.5 for mapping the persuasiveness score to binary label (i.e., persuasive or not). Since the persuasiveness score is an average from three annotators, more than 0.5 means that at least two people agree that the image somewhat improves the persuasiveness (giving a score ≥ 1) or at least one person is convinced by the image (giving a score ≥ 2). Image content types have the distribution of Symbolic photo (23.43%), Scene photo (21.93%), Anecdote (19.84%), Slogan (14.76%), Testimony (10.87%), Statistics (7.28%), Other (1.89%). We observe that images (i.e., symbolic photo/scene photo) occupy a high proportion of the samples. In contrast, data evidence (i.e., statistics) takes the relatively lowest ratio. One potential reason is that social media contents like tweets are generally short and informal, which prefers relatively simple evidence. Note that there are 19 "other" annotations that the annotator was confused about; however, it indicates that our image content type scheme works very well as only 1.89% are out of our defined labels. Finally, as for image persuasion mode, we have 37.85% logos, 50.60% pathos, and 11.55% ethos.

We show how the stance impacts other dimen-

sions. The distributions of different dimensions in terms of stances are shown in Figure 8. For the image contents, tweets opposing *gun control* use significantly more images in the content of Symbolic photos, Anecdote, and Testimony. With respect to supporting ones, they prefer images in the content of Scene photos and Statistics. For image persuasiveness, persuasive rates for both stances are almost the same, which indicates that images are generally used to support both positive and negative arguments. For the persuasion mode, images in supporting tweets use more Logos, more Pathos, and less Ethos than those in opposing tweets.

To further study the relevance between our image content type and its persuasion mode, we report the distributions of content types within each persuasion mode, as shown in Figure 10. In terms of Logos, most samples use statistics and anecdote evidence. It meets the intuition since the logic can usually be clarified by invoking anecdotes and justified by providing supportive number. In terms of Pathos, the majority of samples utilize symbolic and scene photos. This is also reasonable since photographs generally invoke emotional impacts by presenting the most vivid vision information. In terms of Ethos, testimony takes the most ratio since statements from authorities can always enhance trustworthiness. These correlations imply the mutual influences between our annotation dimensions, which raises demands for further study.

5 Experiments

5.1 Models and Tasks

We evaluate our dataset on *gun control* topic based on classification tasks for Stance, Image Persuasiveness, Image Content, Logos, Pathos, and Ethos. Since data size is relatively small, we use pretrained image encoder (ResNet (He et al., 2016)) and text encoder BERT (Devlin et al., 2018) to fine-tune linear classifiers. For fair comparison, we project both image and text embeddings into 1024 dimension, before feeding into classification layers. We compare task performance on Text Modality (T-M), Image Modality (I-M), Image-Text Multi-modality (M-M). As for baseline (BASE), we report the performance when all samples are predicted as positive for binary classification, or predicted as the majority label for multi-class classification.

In the implementation, we follow annotation convention that sets the threshold γ equal to 0.5 to encode persuasiveness scores into binary. For im-

Task	Model	Precision	Recall	F1	AUC
Stance	BASE	0.47 \pm 0.02	1.0 \pm 0.0	0.639 \pm 0.02	/
	T-M	0.501 \pm 0.05	0.74 \pm 0.03	0.596 \pm 0.04	0.527 \pm 0.04
	I-M	0.443 \pm 0.08	0.147 \pm 0.03	0.218 \pm 0.04	0.472 \pm 0.05
	M-M	0.414 \pm 0.04	0.369 \pm 0.06	0.39 \pm 0.05	0.417 \pm 0.03
Persua.	BASE	0.257 \pm 0.03	1.0 \pm 0.0	0.408 \pm 0.04	/
	T-M	0.260 \pm 0.01	0.725 \pm 0.11	0.380 \pm 0.01	0.502 \pm 0.03
	I-M	0.313 \pm 0.02	0.196 \pm 0.05	0.238 \pm 0.05	0.528 \pm 0.03
	M-M	0.296 \pm 0.05	0.486 \pm 0.05	0.364 \pm 0.03	0.534 \pm 0.04
Content	BASE	0.041 \pm 0.0	0.167 \pm 0.0	0.066 \pm 0.0	/
	T-M	0.198 \pm 0.08	0.201 \pm 0.03	0.165 \pm 0.03	/
	I-M	0.235 \pm 0.09	0.204 \pm 0.02	0.151 \pm 0.02	/
	M-M	0.200 \pm 0.02	0.179 \pm 0.01	0.165 \pm 0.01	/
Logos	BASE	0.405 \pm 0.05	1.0 \pm 0.0	0.575 \pm 0.05	/
	TM	0.364 \pm 0.08	0.613 \pm 0.13	0.456 \pm 0.10	0.439 \pm 0.08
	TM	0.351 \pm 0.22	0.097 \pm 0.07	0.144 \pm 0.10	0.406 \pm 0.08
	M-M	0.262 \pm 0.27	0.047 \pm 0.05	0.077 \pm 0.08	0.508 \pm 0.06
Pathos	BASE	0.554 \pm 0.04	1.0 \pm 0.0	0.712 \pm 0.04	/
	T-M	0.613 \pm 0.11	0.714 \pm 0.08	0.658 \pm 0.09	0.582 \pm 0.1
	I-M	0.666 \pm 0.09	0.184 \pm 0.07	0.28 \pm 0.07	0.593 \pm 0.09
	M-M	0.471 \pm 0.42	0.071 \pm 0.1	0.114 \pm 0.15	0.507 \pm 0.12
Ethos	BASE	0.128 \pm 0.04	1.0 \pm 0.0	0.226 \pm 0.06	/
	T-M	0.168 \pm 0.05	0.817 \pm 0.15	0.272 \pm 0.06	0.580 \pm 0.09
	I-M	0.244 \pm 0.16	0.233 \pm 0.16	0.221 \pm 0.13	0.459 \pm 0.18
	M-M	0.124 \pm 0.15	0.083 \pm 0.11	0.098 \pm 0.12	0.450 \pm 0.09

Table 4: Classification benchmark results with standard deviation on *ImageArg* dataset. The reported persuasiveness results use threshold $\gamma = 0.5$.

Threshold (γ)	Pos. Ratio	F1 Score		
		T-M	T-M	M-M
0.1	66.50%	0.681 \pm 0.02	0.265 \pm 0.05	0.536 \pm 0.03
0.3	43.37%	0.538 \pm 0.03	0.251 \pm 0.04	0.459 \pm 0.05
0.5	25.8%	0.380 \pm 0.01	0.238 \pm 0.05	0.364 \pm 0.03
0.7	14.1%	0.246 \pm 0.02	0.168 \pm 0.04	0.233 \pm 0.01
0.9	7.48%	0.138 \pm 0.03	0.084 \pm 0.03	0.115 \pm 0.01

Table 5: F1 scores with standard deviation and positive label ratio for persuasiveness classification with respect to different threshold (γ).

age content classification, we remove 19 examples labeled with “other”. We remove Emoji, URLs, Mentions, and Hashtag in raw tweets, and conduct image augmentation (i.e., horizontal-flip) on the training set, and resize images to 224 \times 224. We implement our models in Pytorch, and run our models on a GeForce RTX 3080 GPU with 12G Memory. We freeze 12-layer transformer blocks in BERT and image encoders while training classifiers. We optimize the networks using Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$. The learning rate is set as 0.001 and the batch size is 16. We conduct 5-fold cross-validation with 80% for training and 20% for testing. We report 5-fold average precision, recall, f1, and AUC score for binary classification, and macro precision, recall, and f1 scores for multi-class classification tasks.

5.2 Quantitative Results Analysis

The results in Table 4 show the classification results. **Task-Stance** Regarding stance, T-M has the

highest performance in terms of AUC scores. It reveals that the image information is redundant to the text for identifying the stance; moreover, the image might introduce disturbing noise due to limited training samples. **Task-Persuasiveness** As for persuasiveness task, we observe that M-M performs slightly poorer than T-M regarding F1 score but relatively better in AUC score. This is because persuasiveness (positive/negative) labels are unbalanced if we use $\gamma = 0.5$ (as shown in Table 3). We show F1 scores drop with respect to thresholds decrease from 0.1 to 0.9 in Table 5. **Task-Content**

In terms of 6-class classification for image content, although all modalities outperform the baseline, the task is shown to be very challenging. It is surprising that the performance with I-M is lower than T-M. The reason might be that visual argumentative tasks demand more specific image encoders that learn sufficient knowledge on persuasiveness and social science; however, the used image encoder is pretrained on a general object detection task on the ImageNet (Krizhevsky et al., 2012), thus the model is unable to learn enough knowledge for our argumentative task with very limited training data. **Task-Logos** Regarding logos, we observe that M-M gains the best AUC score but I-M has lower AUC than text modality. The reason might be that logos images usually contain statistic charts (as shown in Figure 10) that are relatively more difficult to encode than normal images (e.g., images with explicit objects), but multi-modal models might learn these patterns directly from textual inputs. **Task-Pathos** As for pathos, I-M has the best performance in terms of AUC score, and T-M is quite close to I-M while M-M has the lowest. This suggests that the multi-modal representation fusion method we used might be too weak to conduct complex reasoning on the pathos task. **Task-Ethos** The best performance in ethos is from T-M. It is intuitive because the image encoder that was pre-trained on object detection is unable to recognize the optical characters on the image, while this kind of images are common in ethos.

5.3 Qualitative Results Analysis

We conduct qualitative analysis by retrieving the most persuasive images given a text. We run the best pretrained persuasiveness model on test set on each fold (out of 5 folds). Figure 11 shows the actual image, top and bottom images with the highest (0.684) and lowest (0.326) scores, respectively. It

Every day, 100 people are shot and killed. 40,000 are killed each year. But Judge Barrett would rule to gut both our gun safety laws and our access to healthcare. We don't need a reckless, undemocratic nominee who threatens our livelihoods! #WeDissent #BlockBarrett

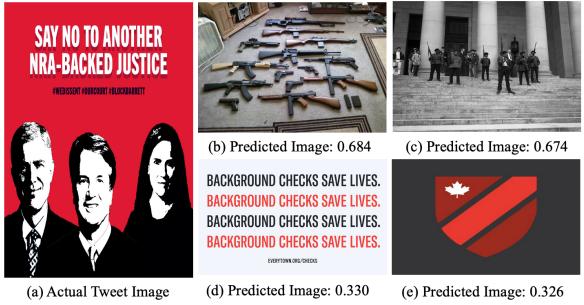


Figure 11: (a) the actual tweet image annotated with persuasiveness score 0 in *ImageArg*; (b) and (c) with top predicted persuasiveness scores; (d) and (e) with lowest predicted persuasiveness scores while retrieving images given the same tweet.

is interesting to find that images with specific objects or scenes (image (b), and (c) in Figure 11) can boost the persuasiveness; however, images with slogans or symbolism have lower scores (image (d), and (e) in Figure 11). This indicates that our image encoder is capable of capturing object information but not optical characters on images (e.g., slogans); therefore, our retrieved images with best persuasion scores are mostly related to gun-object images. Learning an image encoder pre-trained on slogans and visual symbolism is a promising future direction to improve the performance. Another future work could be extracting text information from images by OCR tools and use it as an auxiliary modality to help models learn the context.

6 Conclusion and Future Work

We create a new multi-modal persuasiveness dataset *ImageArg* that focuses on the image functionality and persuasion mode for persuasive arguments. We extend the argumentative annotation scheme from text to vision, and demonstrate its feasibility. We then establish a benchmark on our defined argumentative tasks using computational models, with several input modalities. Our experimental results reveal that the image persuasiveness mining tasks are challenging and have ample room for model improvement. We identify the image encoder as a key modeling bottleneck through a series of qualitative and quantitative analysis, which offers a good starting point for further exploration on this rich and challenging topic.

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A Pilot Study on other topics

A.1 Pilot study: Immigration

We randomly choose 100 tweets on the "Immigration" topic for its pilot study. We make a topic-specific instruction for the stance that provides the topic-specific examples. Similarly, we filter the collected tweet with keywords and argumentative scores. We set the threshold of persuasiveness score to 0.9 to select samples with more clear argumentative stances. For the stance and content type, we assign two annotators for each sample; for the persuasion mode, we assign three annotators for each sample. We focus on the most challenging part learned from the pilot study for the "gun control" topic. Specifically, instead of studying the Kappa score on the persuasion mode of images, we directly calculate Krippendorff's alpha scores for three image persuasion modes. The Inter-rater Agreement is shown in Table 6. We observe high Inter-rater Agreements on the stance and content type annotation. However, the agreements on the persuasion modes are still low. Unlike "gun control," which receives the lowest agreement on Pathos, the agreement on Ethos is the lowest in "immigration." One potential reason is that there are not many resources that provide credible and trustworthy resources for the arguments on the topic. This indicates that the different topics might potentially prefer different persuasion modes.

Task	Alpha	Count
stance	61.5	100
content type	65.8	53
logos	56.7	23
pathos	46.0	23
ethos	30.8	23

Table 6: Inter-agreement rate of each annotation task on the topic "immigration." The count represents the number of samples after filtering from previous questions.

A.2 Pilot study: Abortion

We randomly choose 200 tweets on the "Abortion" topic for its pilot study. Same to "Immigration," we make a topic-specific instruction for the stance that provides the topic-specific examples. The samples are collected and filtered in the same way as well. We use the same matrices used for "Immigration." The Inter-rater Agreement is shown in Table 7. We observe similarly high Inter-rater Agreements on the stance. The agreement on the content type is relatively lower than the other two topics. One

main reason is that authors prefer using photos to imply their arguments. Such photos lead to ambiguity between scene photos and symbolic photos. We give several examples in Figure 12. The agreements on the persuasion modes are even lower than in the other two topics. One reason is that the topic is more controversial, and it is more challenging to give a strong argument. In particular, the Logos gets the lowest agreement, demonstrating the relationship between topics and persuasion modes. We plan to investigate these relationships between topics and persuasion modes in our future study.

Task	Alpha	Count
stance	68.7	200
content type	56.6	76
logos	25.0	48
pathos	37.5	48
ethos	28.2	48

Table 7: Inter-agreement rate of each annotation task on the topic "abortion." The count represents the number of samples after filtering from previous questions.

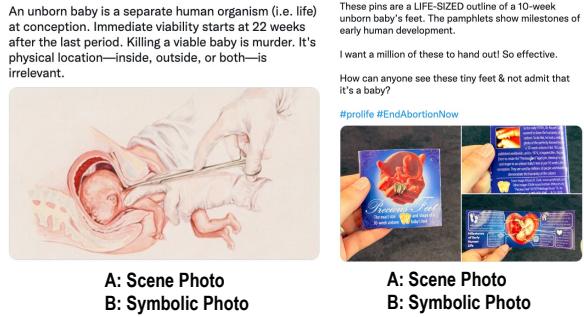


Figure 12: Samples of disagreed on the content type in the topic "abortion."

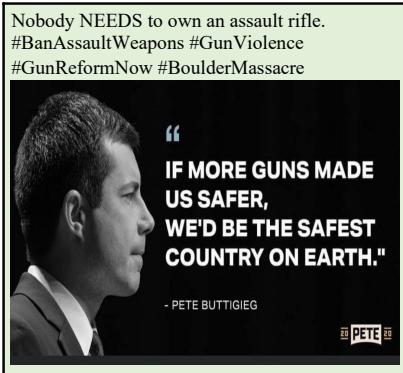
B Coding Manual

B.1 Stance

We setup different instructions for stance annotations on different topics since we would like to provide detailed instructions and examples for different topics separately.

B.1.1 Stance: Gun Control

We aim to study the topic and the stance of tweets. Given a tweet accompanying with an image, you need to answer the stance of the tweet towards a given topic, as depicted in Figure 13.



This tweet _____ the topic "gun control".

- supports
- opposes to
- doesn't hold any stance to
- is not relevant to

Figure 13: Example of stance annotation on gun control

Please make sure that you have the basic knowledge about that social topic and you understand the key message that the tweet (i.e. both the text and the image) sends. Just skip the HIT if you are not sure.

The question is about the stance. You need to decide whether the tweet is relevant or not to the social topic gun control. If it is relevant, then you need to annotate the stance: supports/opposes to/doesn't hold any stance.

A tweet is considered as relevant if it talks about anything that has to do with, but not limited to, the following issue categories: the Second Amendment, Gun control laws, etc. Tweets which contain the following hashtags are probably relevant to gun control: #NoBillNoBreak, #WearOrange, #End-GunViolence, #DisarmHate, #molonlabe, etc.

A tweet should be considered as irrelevant if it mentions a gun death event or a gun violence news, but the context is not necessarily about gun control.

Some examples for relevant tweets and their stance (we only show the text here, but you need to answer this question from both the text and image):

- “*Standing up for the second amendment and carrying a firearm for self defense.*” This tweet asks the audience to stand up for the 2nd amendment, which opposes to gun control;
- “*I don't understand why we can't ban assault weapons. We all know they are only used for hunting people. #PrayForOrlando #guncontrolplease.*” This tweet talks about banning weapons and contains the hashtag “#guncontrolplease”, which supports gun control;

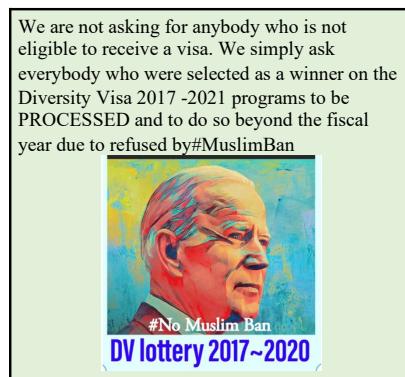
- *A common way to reduce violence in schools is to implement stronger security measures, such as surveillance cameras, security systems, campus guards and metal detectors. #violence #domesticviolence #gun #gunviolence #abuse #people #world #person #workplace.*” This tweet is relevant to the topic, but we are not sure about its stance.

Some examples for non-relevant tweets (we only show the text here, but you need to answer this question from both the text and image):

- “*Love will always conquer hate. #PrayForOrlando #OrlandoShooting.*” This tweet talks about gun violence but not about gun control;
- “*#Gunviolence has serious and lasting social and emotional impacts on those who directly and indirectly experience it.*” This tweet points out the impact of gun violence but not about gun control.

B.1.2 Stance: Immigration

We aim to study the topic and the stance of tweets. Given a tweet accompanying with an image, you need to answer the stance of the tweet towards a given topic, as depicted in Figure 14.



This tweet _____ the topic "immigration".

- supports
- opposes to
- doesn't hold any stance to
- is not relevant to

Figure 14: Example of stance annotation on immigration

Please make sure that you have the basic knowledge about that social topic and you understand the key message that the tweet (i.e. both the text and the image) sends. Just skip the HIT if you are not sure.

The question is about the stance. You need to decide whether the tweet is relevant or not to the social topic immigration. If it is relevant, then you need to annotate the stance: supports/opposes to/doesn't hold any stance.

A tweet is considered as relevant if it talks about anything that has to do with, but not limited to, the following issue categories: Borders, Birthright citizenship, Immigrant Crime, DACA and the DREAM Act, Deportation debate, Economic impact, Immigration quotas, Immigrants' rights and access to services, Labor Market - American workers and employers, Law enforcement, Refugees, etc.

A tweet should be considered as irrelevant if it mentions a group of immigrant people such as Muslim, Syrian refugees but doesn't explicitly talk about immigration issues.

Some examples for relevant tweets and their stance (we only show the text here, but you need to answer this question from both the text and image):

- “*Man feels bad for new immigrant driver in Brampton that crashed into his truck, causing \$6K worth of damages - he had no licence or insurance*”. This tweet is related to the topic of immigration under the category of Immigrant Crime, and it opposes to immigration.
- “*House Bill 3438 will finally give our immigrant students some desperately needed resources! Thank you State Representative Maura Hirschauer for introducing this bill! Now, let's make sure this bill becomes law!*” This tweet is related to the topic of immigration under the category of DREAM Act, and it supports immigration.
- “*I'm a woman that supports Trump to fix economy, immigration, school, military more. #MAGA3X*” We consider a tweet as relevant even if it mentions several topics in addition to immigration, and it opposes to immigration.

Some examples for non-relevant tweets (we only show the text here, but you need to answer this question from both the text and image):

- “*'Will I die, miss?' Terrified Syrian boy suffers suspected gas attack.*” This tweet talks about a Syrian boy suffering a gas attack, which may be pointing to a war or terrorist event in Syria, not necessarily directly about an immigration issue.

- “*Virtual tour of Steinbach, in partnership with MANSO, Welcome Place, Eastman Immigrant Services and the Steinbach LIP, coming up March 9th, 2021. It's free so don't miss out!*” This tweet mentions Immigrant Services, but does not talk about any immigration issue.
- “*I called on [USERNAME] for increased vaccine access for South Philadelphia seniors and for members of our immigrant communities. We can't let physical distance and language barriers keep people from this lifesaving vaccine.*” This tweet talks about vaccine access for the immigrant community but it doesn't hold any stance towards any immigration policy.

B.1.3 Stance: Abortion

We aim to study the topic and the stance of tweets. Given a tweet accompanying with an image, you need to answer the stance of the tweet towards a given topic, as depicted in Figure 15.



This tweet _____ the topic "Abortion".

- supports
- opposes to
- doesn't hold any stance to
- is not relevant to

Figure 15: Example of stance annotation on abortion

Please make sure that you have the basic knowledge about that social topic and you understand the key message that the tweet (i.e. both the text and the image) sends. Just skip the HIT if you are not sure.

The question is about the stance. You need to decide whether the tweet is relevant or not to the social topic immigration. If it is relevant, then you need to annotate the stance: supports/opposes to/doesn't hold any stance.

A tweet is considered as relevant if it talks about anything that discusses whether the abortion should be a legal option. If the arguments in the tweet text and image support that the abortion should be

a legal option, then please choose “supports”; if arguments oppose to legal abortion, then choose “opposes to”; if arguments doesn’t hold any stance for the topic then choose “doesn’t hold any stance”. Notice that a tweet is considered as irrelevant if it doesn’t directly discuss whether the abortion should be a legal option or not, even though it may talk about related topics such as babies born alive after an abortion , birth control, etc.

B.2 Persuasiveness level and image content

We aim to study the persuasiveness level of images in tweets as well as their content. Given a tweet text shown as Figure 16, you need to give a persuasiveness score of it.

Nobody NEEDS to own an assault rifle.
#BanAssaultWeapons #GunViolence
#GunReformNow #BoulderMassacre

Figure 16: Example of a text only tweet

Then given a tweet accompanying an image shown as Figure 17, you need to give a persuasiveness score again.

Nobody NEEDS to own an assault rifle.
#BanAssaultWeapons #GunViolence
#GunReformNow #BoulderMassacre

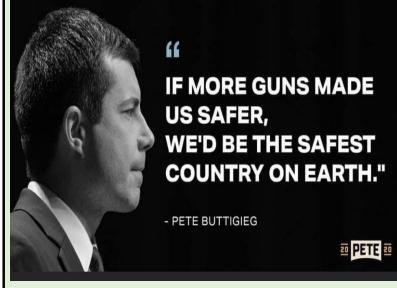


Figure 17: Example of a tweet accompanying an image

Finally, you need to select the content type of the image. The content type of an image represents what type of the information the image mainly carries. Specifically, you need to pick one out of six types below for each image.

Statistics: the image provides evidence by **stating or quoting quantitative information**, such as a chart/data analysis, that is related to the tweet text.

An image could be considered statistics if: 1) It carries quantitative information (number/statistics/etc). 2) The key purpose of the image is to deliver this quantitative information, in the case there are multiple content types involved.

For the examples shown in Figure 18, in the statistics example, the image mainly shows a chart and delivers quantitative information (homicides by firearm per 1 million people). In contrast, in the NOT statistics example, though there are numbers in the image, the main information is a news title and the shooting scene, but not these numbers.

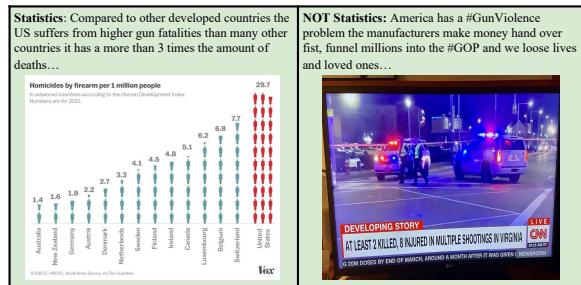


Figure 18: Example of tweets with statistics image and a non-statistics image.

Testimony: the image **quotes statements or conclusions from an authority**, such as a piece of an article/claim from an official document, that is related to the tweet text.

The image can be considered as testimony if: 1) The content contains texts such as statements/conclusions/pieces of article. 2) These texts are original from other resources such as news/celebrities/official documents/etc. 3) The key purpose of the image is to quote the authorized statement, in the case there are multiple content types involved.

For the examples shown in Figure 19, in the Testimony tweet example, the image mainly cites a statement given by the transportation secretary. However, in the NOT Testimony tweet example, though it contains a piece of texts, these texts are not cited from an authority, therefore, it is not testimony.



Figure 19: Example of tweets with testimony image and a non-testimony image.

Anecdote: the image provides information based on the **author's personal experience**, such

as facts/personal stories, that are related to the tweet text.

An image can be considered as an anecdote if : 1) It delivers a personal experience, Or 2) it shows a fact/experience that comes from personal view/known by the author. 3) The key purpose of the image is to deliver personal experience, in the case there are multiple content types involved.

For the examples shown in Figure 20, the anecdote image shows the personal view on the fact that guns have been developed since the period of the 2nd amendment, and therefore the laws for guns should be developed as well. However, in the NOT anecdote example, though it comes from a personal statement, it does not describe any fact/experience/stories.



Figure 20: Example of tweets with anecdote image and a non-anecdote image.

Slogan: the image expresses a piece of advertising phrase.

An image can be considered as a slogan if: 1) It mainly delivers a piece of text as slogan; 2) The text is for advertising purposes as an advertising phrase/claim/statement. 3) The key purpose of the image is to deliver the piece of text, in the case there are multiple content types involved.

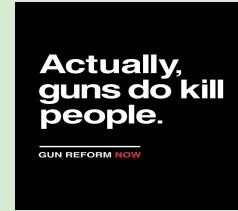
For the examples shown in Figure 21, the slogan image presents a phrase “Actually gun do kill people. Gun Reform Now”, therefore it is a slogan. However, For the example of NOT Slogan, though the image is for advertising, it does not contain a phrase for that, therefore it is not a slogan.

Scene photo: the image shows a literal scene/photograph that is related to the tweet text.

An image can be considered as a scene photo if: 1) It shows a literal photograph/scene. 2) The image is directly related to the text. 3) The key purpose of the image is to deliver the image content but not the text within, in the case there are multiple content types involved.

Symbolic photo: the image shows a sym-

Slogan: New research shows that the US has so much #gunViolence because of GUNS! Make our country safer for everyone. Demand #GunControlNow #EnoughIsEnough...



NOT Slogan: Thanks for all your Thoughts and Prayers. They are saving lives right and left. Clearly. #GunControlNow #BoulderStrong #GunViolence



Figure 21: Example of tweets with slogan image and a non-slogan image.

bol/art that expresses the author’s viewpoints in a **non-literal** way.

An image can be considered as a symbolic photo if: 1) It shows a symbol/art. 2) It expresses the viewpoint from the author in an implicit way. 3) The key purpose of the image is to deliver the image content but not the text within, in the case there are multiple content types involved.

For example, in the figure 22, the scene photo image shows a real photograph of a gun violence scene reported by CNN news. In the Symbolic photo, though relevant to the text, it shows a photo/image that is related to the text in a non-literal way (blood signifies gun-killing and the hand posture signifies praying), therefore it is not a scene photo but a symbolic photo.

Scene photo: America has a #GunViolence problem the manufacturers make money hand over fist, funnel millions into the #GOP and we loose lives and loved ones...



Symbolic photo: Thanks for all your Thoughts and Prayers. They are saving lives right and left. Clearly. #GunControlNow #BoulderStrong #GunViolence



Figure 22: Example of tweets with scene photo image and a symbolic photo image.

The key difference between the Scene photo and Symbolic photo is **whether the photograph sends a message literally or symbolically**. For a scene photo, the image directly expresses/supports the author’s view without any rhetoric; for a symbolic photo, the image may have several possible interpretations and the audience can understand its symbolic meaning after considering the tweet text. Consider the example shown in the figure 23: for the scene photo, it directly shows a protest scene and the author opposes to the abortion by considering it

as a lie. In the symbolic photo, the author shows a photo of Notre Dame as a symbol of anti-abortion. The photo is not directly related to abortion, but audience can understand its symbolic meaning after reading the text.



Figure 23: Another example of tweets with scene photo image and a symbolic photo image.

In the case there are multiple content types involved: You need to first identify the key purpose of the image (i.e. what is the most important information in the image). Then please select the content type of the key purpose. Table 8 shows the summary of content types for each key purpose.

Table 8: Summary of content types for each key purpose

Key Purpose	Content Type
Quantitative information in the image	Statistics
Textual information in the image	Testimony Anecdote Advertising phrases
Graphical information in the image	Scene Photo Symbolic Photo
Literal photograph	
Non-literal/rhetorical photograph	

B.3 Persuasion Mode

We aim to study the **argumentative roles of images** in tweets. Given a tweet accompanying an image, we would ask you to choose the persuasion mode of the image. The persuasion mode of an image represents how the image convinces the audience. Specifically, we will ask you whether the image appeals to logic/emotion/credibility. Additionally, we will ask you why you make the choices.

Q1: Does the image make the tweet more persuasive by appealing to **logic and reasoning?**

The image appeals to logic and reasoning if it persuades audiences with reasoning from a fact/statistics/study case/scientific evidence. Specifically, if: 1) the image **contains information for logic and reasoning**; 2) the image **presents logic and reasoning**.

Also, we will ask you why you made the choice. i.e. Describing the logic/reasoning brought by the

image. Such as following, by filling the blank in the textbox:

The logic/reasoning of the image is [the correlation between gun deaths and gun ownership by population].

For example shown in Figure 24, the left image provides a chart that shows the high gun deaths and the high gun ownership by the population of the US, which implies [a correlation between gun death and gun ownership which demonstrates that there will be less gun deaths with gun control]. On the contrary, the right image shows the scene of the shooting but does not provide any reasoning or logic.

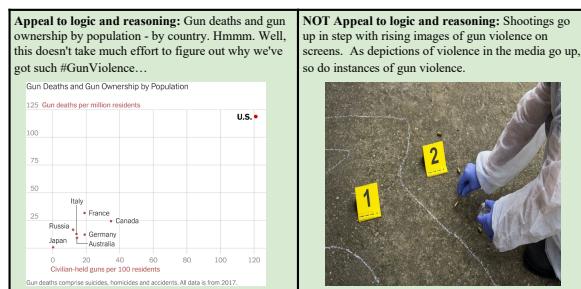


Figure 24: Example of tweets with logos image and non-logos image.

Q2: Does image make the tweet more persuasive by appealing to **emotion?**

The image appeals to **emotion**, if it puts audiences in a certain frame of mind by stimulating them to identify/empathize/sympathize with the arguments.

Specifically, if : 1) the image **invokes the audience with strong emotion**, such as sadness, happiness, compassion, worriness; 2) the image **makes the audience identify/empathize/sympathize** with the author/arguments.

Also, we will ask you why you made the choice. i.e. Describing the emotion(such as anger/amusement/sad/etc.) or impulsion(desire to do something) brought by the image. Such as following, by filling the blank within the [bracket]:

The image evokes my emotion/impulse of [anger].

For example shown in Figure 25, the left image shows the grieved "Uncle Sam" saying "no" with helplessness, which evokes the [desire for gun control]. The right image provides an item that can revoke [compassion and forgiveness].

Q3: Does image make the tweet more persuasive by **enhancing credibility and trustworthiness?**



Figure 25: Example of tweets with pathos images.

The image **enhances credibility and trustworthiness**, if it makes people trust something more via authorized/trusted expertise/title/reputation.

Specifically, if 1) The image **cites reliable sources** of the event/story/opinion/stance, that can make the contents trustworthy. Reliable sources include news, research reports, celebrated dictum, etc. Sources which are not proved/well-known by the audience (.e.g. an organization logo) are not considered as reliable. 2) the image **shows authorities** that can convince the audience to believe the arguments.

Also, we will ask you why you made the choice. i.e. Describing the resources of the citation that enhances the credibility. Such as following, by filling the blank within the [bracket]:

The credibility is enhanced by [a citation to political report]

For example shown in Figure 26, the left image takes a screenshot of the source of a report from [New York Times], which increases credibility. The NOT Ethos right image shows the views but are not quoted sentences that do not provide the credibility to enhance the argument.

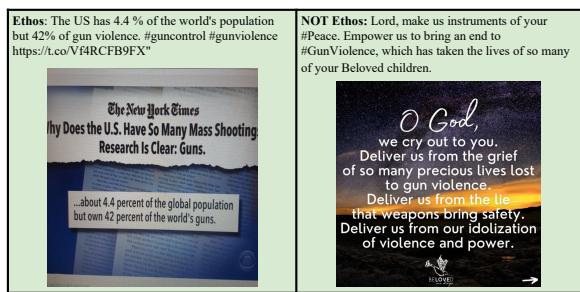


Figure 26: Example of tweets with ethos image and non-ethos image.