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

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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. To expand persuasiveness mining into 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 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 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 annotations, 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 Fig. 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, 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 (Sec. 3.3) that explicitly identifies image functionalities from a persuasive perspective. Furthermore,

![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.](image-url)
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 multimodal 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. Our code and data is publicly available at: https://github.com/MeiqiGuo/ArgMining2022-ImageArg.

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., 2019). 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 mainstream, 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 representations of each modality and developing effective fusion methods (Tsai et al., 2018; Hu et al., 2019; Tan and Bansal, 2019; Lu et al., 2020). 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
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 Fig. 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 Fig. 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.

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 $\gamma$. We use $\gamma = 0.5$ when we annotate data and test with different $\gamma$ values for persuasiveness classification task (Table 6).

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

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

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 follows:

- **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 audi-
ences 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 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 keywords through TwitterAPI. The raw data (286k tweets) are collected in a two-year window from 3/29/2019 to 3/29/2021. We retain tweets whose texts tend to be argumentative, with an argument confidence score larger than 0.9 by using ArgumentText Classify API. 99.48% of tweets are discarded for having an argument confidence score below 0.9. These filtering processes ensure our annotation data has high argumentation-confidence and topic-relevance.

#### 4.2 Annotation Strategies

We develop annotation strategies based on several rounds of pilot annotations. To ensure the annotation quality, we provide coding manual and examples for annotators (see the Appendix A for details). We employ qualified workers who passed a qualitative test that evaluates the workers’ understanding on our annotation manual.

We start with the topic of gun control. In the first-round, we distribute 87 samples to two random annotators on MTurk. Table 1 shows Krippendorff’s alpha (Krippendorff, 2011) score for inter-rater agreement. Based on the interpretation of alpha scores in Landis and Koch (1977); Hartling et al. (2012), we conclude that stance and content type have a substantial inter-agreement but persuasion mode inter-agreement is slight. To investigate this issue, we modify our annotation guideline for persuasion mode. Instead of using three-class annotation (i.e., choosing one persuasion mode from 3 options), we move to three-label annotation that asks a binary question for each mode for each sample (i.e., annotating yes/no for each persuasion mode, individually). Moreover, the annotators are required to justify their choices by giving short comments. The improved results (on the final corpus from Sec. 4.3) are shown in Table 2, although the persuasion mode agreement (i.e., Logos, Pathos, and Ethos) is still lower than stance and content type. This is likely because annotators have different emotional reasoning (i.e., some annotators are easily evoked by images while others are not).

| 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.

| 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.

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1 We use keywords provided in Guo et al. (2020)’s work.
2 https://developer.twitter.com/en/docs/twitter-api
3 https://api.argumentsearch.com

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4 Note that the availability of annotation questions is based on the answer to the prior questions (Fig. 2) therefore each task has different sample numbers.
Figure 7: Annotator A annotates the above images as Pathos because these examples express emotions, while annotator B disagrees and marks as not Pathos.

For example, one annotator recognized strong emotional impact (e.g., togetherness, sadness, anxiety, etc.), while the other not as shown in Fig. 7.

We further perform pilot annotations for the topics of immigration and abortion, with the best annotation strategies that we developed for annotating gun control. We randomly choose 100 or 200 tweets respectively on immigration or abortion for the pilot study, and make a topic-specific instruction for the stance annotation that provides some topic-specific examples. The Inter-rater Agreement for both topics is shown in Table 3. We observe high Inter-rater Agreements on the stance annotation, which demonstrates the utility of our topic-specific instructions. The agreement on the content type is generally good, however, abortion has relatively lower agreement than the other two topics. One main reason is that authors prefer using photos to support their arguments. Such photos lead to ambiguity between scene photos and symbolic photos, as examples shown in Fig. 8. Moreover, we notice that the agreements on the persuasion modes are not satisfying. For immigration, Ethos has the lowest agreement, and one explanation is that there are few authentic resources that provide credible and trustworthy arguments on this topic; for abortion, the agreement on all three persuasion modes are relatively low, in particular, Logos surprisingly gets the lowest agreement.

These studies indicate that the inter-rater agreement on annotating persuasion mode is topic-dependent, and the relationship between topics and persuasion modes needs further investigation. 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 support or oppose stance on gun control topic. 36% of data is discarded for not having an agreed support/oppose stance. We report the distribution of each annotation scheme in Fig. 9, and the inter-rater agreement evaluation in Table 2. The results reveal that the annotators have substantial agreement on the stance and content types, and moderate agreement on the image persuasion mode. Specifically, the stance annotations are balanced distributed as shown in Fig. 9 (a): 46.3% support and 54.7% oppose. As for image persuasiveness annotations, Table 4 shows sample distributions in different persuasiveness score intervals. We use a threshold $\gamma$ to discretize numerical persuasiveness scores to binary labels (i.e., persuasiveness or not). The $\gamma$ is set to 0.5 in our annotations since the persuasiveness score is an average of three annotators, thus $\gamma$ greater than 0.5 suggests that there is at least two annotators annotating images persuasiveness with L1 or higher ($\geq 1$) scores (as defined in Sec. 3.2) or at least one annotator annotating L2 or higher scores ($\geq 2$). In terms of image content types, its distribution is shown in Fig. 9 (b): 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 low 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
Figure 9: Distributions of (a) stance, (b) image content type, and (c) persuasion mode in our corpus on gun control topic.

Figure 10: Distributions of (a) image persuasiveness, (b) content type and (c) persuasion mode regarding stances (support in blue and oppose in red) in our corpus on gun control topic.

| Persuasiveness Score | Count | Percentage |
|----------------------|-------|------------|
| 0.0 - 0.1            | 336   | 33.50%     |
| 0.1 - 0.3            | 232   | 23.13%     |
| 0.3 - 0.5            | 176   | 17.55%     |
| 0.5 - 0.7            | 118   | 11.76%     |
| 0.7 - 0.9            | 66    | 6.58%      |
| ≥ 0.9                | 75    | 7.48%      |

Table 4: The annotated image persuasiveness score distribution on gun control topic in ImageArg.

“other” out of 1003 annotations that annotators were confused about; however, it does suggest that our image content type scheme works very well as only 1.89% are out of our defined labels. In terms of image persuasion mode, we only annotate images with persuasiveness score $\gamma$ greater than 0.5, which produces 259 samples. As shown in Fig. 9 (c), we have 37.85% Logos, 50.60% Pathos, and 11.55% Ethos.

Additionally, we show how the stance impacts image persuasiveness, content type, and persuasion mode. In Fig. 10 (a), supporting and opposing gun control stance are almost evenly distributed with respect to persuasiveness and non-persuasiveness, which suggests that images generally support both positive and negative arguments. For the image content type in Fig. 10 (b), opposing gun control stance uses significantly more images with respect to Symbolic photos, Anecdote, and Testimony; however, supporting stance prefers images in the content of Scene photos and Statistics. Regarding persuasion mode in Fig. 10 (c), images in supporting gun control stance uses more Logos and Pathos but less Ethos than those in the opposing stance.

To further study the relevance between image content type and persuasion mode, we report their correlated distributions in charts. Fig. 11 (a) shows that most Logos samples use Statistics and Anecdote evidence. It meets the intuition that the logical reasoning can usually be clarified by introducing anecdotes and justified by providing supportive statistics. In terms of Pathos in Fig. 11 (b), the majority of samples utilize Scene and Symbolic photos. This is also reasonable since images generally promote emotional impression by presenting visual information. Regarding Ethos, Fig. 11 (c) shows Testimony takes the most ratio because statements from authorities can enhance trustworthiness. These correlations imply mutual influences between different annotation dimensions and raise demands for further study.

5 Experiments

5.1 Models and Tasks

We evaluate our corpus on gun control topic with binary classification tasks for Stance, Persuasiveness, Logos, Pathos, and Ethos and multi-class classification task for Image Content. Since data size is relatively small, we use pretrained image encoder ResNet50 (He et al., 2016) and text encoder BERT (Devlin et al., 2019) to fine-tune linear classifiers.
We conduct 5-fold cross-validation (80% data in train; 20% data in test). We report 5-fold average performance on Text Modality (T-M), Image Modality (I-M), and Image-Text Multi-modality (M-M) that concatenates T-M and I-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. We don’t use the majority baseline for the binary classification task because the recall and F1 scores are always 0 if the majority label is negative, which is not interesting to compare with.

In the implementation, we follow the annotation strategy (Sec. 4.2) that uses threshold $\gamma$ equal to 0.5 to encode persuasiveness scores into binaries. We remove Emoji, URLs, Mentions, and Hashtags in tweet texts, and discard 19 samples labeled with “Other” for the image content classification task. All images are resized to 224x224 dimension, and augmented (i.e., horizontal-flipped) only in training. Our models are implemented with Pytorch, and trained on a GeForce RTX 3080 GPU. We freeze BERT and ResNet50 encoders while training classifiers, and optimize the networks using Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$. The learning rate is 0.001 and the batch size is 16. We conduct 5-fold cross-validation (80% data in train; 20% data in test). We report 5-fold average Precision, Recall, F1, and AUC scores for binary classification and macro Precision, Recall, and F1 scores for multi-class classification on the test set.

### 5.2 Quantitative Results Analysis

Table 5 shows the classification benchmark results with standard deviation on gun control topic in ImageArg corpus.

**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 4). We show F1 scores drop with respect to threshold increases from 0.1 to 0.9 in Table 6.

**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

| Task       | Model  | Precision | Recall | F1    | AUC   |
|------------|--------|-----------|--------|-------|-------|
| Stance     | T-M    | 0.504(0.05) | 0.70(0.01) | 0.59(0.04) | 0.527(0.04) |
|            | I-M    | 0.443(0.00) | 0.473(0.05) | 0.418(0.04) | 0.472(0.05) |
|            | M-M    | 0.414(0.00) | 0.390(0.03) | 0.400(0.05) | 0.417(0.03) |
| Persuasion | T-M    | 0.206(0.00) | 0.725(0.11) | 0.380(0.01) | 0.502(0.03) |
|            | I-M    | 0.313(0.02) | 0.497(0.01) | 0.298(0.05) | 0.528(0.03) |
|            | M-M    | 0.296(0.00) | 0.486(0.05) | 0.364(0.03) | 0.534(0.04) |
| Content    | T-M    | 0.198(0.00) | 0.201(0.01) | 0.165(0.03) | 0.165(0.03) |
|            | I-M    | 0.235(0.00) | 0.204(0.03) | 0.153(0.02) | 0.153(0.02) |
|            | M-M    | 0.200(0.00) | 0.179(0.01) | 0.165(0.03) | 0.165(0.03) |
| Logos      | T-M    | 0.304(0.00) | 0.613(0.11) | 0.436(0.10) | 0.439(0.08) |
|            | I-M    | 0.301(0.02) | 0.497(0.07) | 0.414(0.10) | 0.406(0.06) |
|            | M-M    | 0.262(0.00) | 0.464(0.05) | 0.377(0.08) | 0.508(0.06) |
| Pathos     | T-M    | 0.613(0.11) | 0.714(0.08) | 0.689(0.09) | 0.582(0.10) |
|            | I-M    | 0.666(0.09) | 0.184(0.02) | 0.280(0.07) | 0.593(0.09) |
|            | M-M    | 0.471(0.02) | 0.170(0.08) | 0.114(0.15) | 0.507(0.12) |
| Ethos      | T-M    | 0.108(0.00) | 0.817(0.15) | 0.272(0.06) | 0.580(0.09) |
|            | I-M    | 0.244(0.16) | 0.233(0.15) | 0.223(0.13) | 0.459(0.18) |
|            | M-M    | 0.124(0.15) | 0.083(0.11) | 0.098(10.12) | 0.450(0.09) |
We conduct qualitative analysis by retrieving the images given the same tweet text. Specifically, we run the multi-modality (M-M) model, trained using computational models, with multiple input modalities. Our experimental results reveal that image persuasiveness mining is challenging and that there is 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. The first version of ImageArg has 1003 annotations on the gun control topic. In the future work, we will work on constructing datasets on the topics of immigration and abortion, and scaling up the annotations.

| Threshold (γ) | Pos. Ratio T-M | I-M | M-M |
|--------------|---------------|-----|-----|
| 0.1          | 66.50%        | 0.683±0.02 | 0.269±0.05 | 0.539±0.03 |
| 0.3          | 45.37%        | 0.538±0.01 | 0.253±0.04 | 0.459±0.05 |
| 0.5          | 23.8%         | 0.380±0.01 | 0.238±0.05 | 0.364±0.03 |
| 0.7          | 14.1%         | 0.246±0.02 | 0.168±0.04 | 0.233±0.01 |
| 0.9          | 7.48%         | 0.138±0.03 | 0.084±0.03 | 0.117±0.01 |

Table 6: F1 scores with standard deviation and positive label ratio for Persuasiveness classification with respect to different threshold (γ).

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 12: (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 text.
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A Coding Manual

A.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.

A.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. 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 topic of 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, #EndGunViolence, #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 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.

A.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. 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 topic of 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,
We are not asking for anybody who is not eligible to receive a visa. We simply ask everybody who were selected as a winner on the Diversity Visa 2017 -2021 programs to be PROCESSED and to do so beyond the fiscal year due to refused by#MuslimBan

We are not asking for anybody who is not eligible to receive a visa. We simply ask everybody who were selected as a winner on the Diversity Visa 2017 -2021 programs to be PROCESSED and to do so beyond the fiscal year due to refused by#MuslimBan

Figure 14: Example of stance annotation on immigration

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.

A.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. 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 abortion. 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.

A.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.

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.

Anecdote: the image provides information based on the author’s personal experience, such as facts/personal stories, that are related to the tweet text.

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.

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.

**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 guns 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 symbol/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 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.

The key difference between the Scene photo and Symbolic photo is **whether the photograph**
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.

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].

Emotion: A personal narrative - Dr. Sonya Lewis

We must reject helplessness and complacency and we must allow ourselves to feel the raw, sick... etc.

Emotion: Thanks for all your Thoughts and Prayers. They are saving lives right and left. Clearly.

#GunControlNow #BoulderStrong #GunViolence

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

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.

Ethos: The US has 4.4% of the world’s population but 42% of gun violence. #guncontrol #gunviolence

https://t.co/Vf4RCFB9FX

NOT Ethos: Lord, make us instruments of your #Peace. Empower us to bring an end to #GunViolence, which has taken the lives of so many of your Beloved children.

Figure 25: Example of tweets with pathos images.

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