# Predicting the Politics of an Image Using Webly Supervised Data

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# **Abstract**

The news media shape public opinion, and often, the visual bias they contain is evident for human observers. This bias can be inferred from how different media sources portray different subjects or topics. In this paper, we model visual political bias in contemporary media sources at scale, using webly supervised data. We collect a dataset of over one million unique images and associated news articles from left- and right-leaning news sources, and develop a method to predict the image's political leaning. This problem is particularly challenging because of the enormous intra-class visual and semantic diversity of our data. We propose a two-stage method to tackle this problem. In the first stage, the model is forced to learn relevant visual concepts that, when joined with document embeddings computed from articles paired with the images, enable the model to predict bias. In the second stage, we remove the requirement of the text domain and train a visual classifier from the features of the former model. We show this two-stage approach facilitates learning and outperforms several strong baselines. We also present extensive qualitative results demonstrating the nuances of the data.

# 1 Introduction

One of the goals of the media is to inform, but in practice, the media also shapes opinions [23, 53, 2, 20, 57, 44]. The same issue can be presented from multiple perspectives, both in terms of the text written in an article, and the visual content chosen to illustrate the article. For example, when speaking of immigration, left-leaning sources might showcase the struggles of well-meaning immigrants, while right-leaning sources might portray the misdeeds of criminal immigrants. The type of topics portrayed is also strong cue for the left or right bias of the source media (e.g. tradition is primarily seen as a value on the right, while diversity is seen as a value on the left [15]).

In this paper, we present a method for recognizing the political bias of an image, which we define as whether the image came from a left- or right-leaning media source. This requires understanding: 1) what visual concepts to look for in images, and 2) how these visual concepts are portrayed across the spectrum. Note that this is a very challenging task because many of the concepts that we aim to learn show serious visual variability within the left and right. For example, the concept of "immigration" can be illustrated with a photo of a border wall, children crying behind bars while detained, immigration agents, protests and demonstrations about the issue, politicians giving speeches, etc. Human viewers account for such within-class variance by generalizing what they see into broader semantic concepts or themes using prior knowledge, deduction, and reasoning.

On the other hand, modern CNN architectures learn by discovering recurring textures or edges representing objects in the images through backpropagation. However, the same objects might appear and be discussed *across* the political spectrum, meaning that the simple presence or absence of objects

is not a good indicator of the politics of an image. Thus, model training may fall into poor local minima due to the lack of a recurring discriminative signal. Further, it is not merely the presence or absence of objects that matters, but rather *how* they are portrayed, often in subtle ways.

In order to capture the visual concepts necessary to predict the politics of an image, we propose a method which uses an auxiliary channel at training time, namely the article text that the image is paired with. Our method contains two stages. In the first one, we learn a document embedding model on the articles, then train a model to predict the bias of the image, given the image and the paired document embedding. To be successful on this task, the model learns to recognize visual cues which complement the textual embedding and suggest the politics of the image-text pair. At test time, we want to recognize bias from images alone, without any article text. Thus, in the second training stage of the model, we use the first stage model as a feature extractor and train a linear bias classifier on top. The article text serves as a type of privileged information to help guide learning.

Since recognizing the right semantic and visual concepts amidst intra-class variance requires large amounts of data, we train our approach on webly supervised data: the only labels are in the form of the political leaning of the source that the image came from. However, for testing purposes, we collect human annotations and test on images where annotators agreed on the label. We experimentally show that our method outperforms numerous baselines on both a large held-out webly supervised test set, and the set of crowdsourced annotations.

We believe that recognizing the political bias of a photograph is an important step towards building socially-aware computer vision systems. Such awareness is necessary if we hope to use computer vision systems to automatically tag or describe images (e.g. for the visually impaired) or to summarize large collections of potentially biased visual content. Social media companies or search engines may deploy such techniques to automatically identify the political bent of images or even entire news sites being spread or linked to. Progress has already been made in this space in other domains. For example, Facebook automatically determines users' political leanings from site activity and pages liked [40]. Other works have studied predicting political affiliation from text [11, 73, 68] or even MRI scans [58]. However, visual bias understanding has been greatly underexplored. While some work examines visual persuasion [31, 26], none analyzes political leaning as we do.

Our contributions are as follows:

- We propose and make available a very large dataset of biased images with paired text, and a large amount of diverse crowdsourced annotations regarding political bias.
- We propose a weakly supervised method for predicting the political leaning of an image by using noisy auxiliary textual data at training time.
- We perform a detailed experimental analysis of our method on both webly supervised and human annotated data, and demonstrate the factors humans use to predict bias in images.
- We show qualitative results that demonstrate the relationship between images and semantic
  concepts, and the variability in how faces of the same person appear on the left or the right.

#### 2 Related Work

Weakly supervised learning. Our work is in the weakly supervised setting, in the sense that other than noisy left/right labels, our method does not receive information about what makes an image left-or right-leaning. This is challenging because there is significant variety in the type of content that can be left-leaning or right-leaning. Thus, our method needs to identify relevant visual concepts based on which to make its predictions. Recently, weakly supervised approaches have been proposed for classic topics such as object detection [45, 8, 78, 72, 75], action localization [69, 56], etc. Researchers have also developed techniques for learning from potentially noisy web data, e.g. [7]. Also related is work in unsupervised discovery of patterns and topic modeling, e.g. [37, 38, 61, 62, 79, 27, 13, 63, 18]. In contrast to these works, our problem exhibits much larger within-class variance (with left and right being the classes of interest). Unlike objects and actions, the differences between left and right live in semantic space as much as they do in visual space, hence our use of auxiliary training inputs.

**Curriculum learning.** Also relevant are self-paced and curriculum learning approaches [28, 51, 76, 77, 29]. These attempt to simplify learning by finding "easy" examples to learn with first. We too

¹Our dataset, code, and additional materials are available online for download here: http://www.cs.pitt.edu/~chris/politics

employ a type of curriculum learning. We first train a multi-modal classifier to predict bias, using the assumption that the relation between text and bias is more direct. We then leverage this model as a feature extractor by adding an image-only politics classifier on top of it. Thus, our method focuses the model on relevant visual concepts using text.

**Privileged information.** Our method also exploits a similar intuition as privileged information methods [65, 60, 25, 43, 17, 22, 4, 35] that use an extra feature input at training time. These approaches use tied weights [4], computing summary statistics [60, 35], or multitask training [17] to guide learning. The closest such method to ours is [22] which uses an approach trained to predict text embeddings from images. The features are then applied on visual-only data. However, in early experiments we showed directly predicting text embeddings from images is much more challenging on our data because of the many-to-many relationship of images with topics (e.g. image of the White House can be paired with text about Trump's children, border control, LGBT rights, etc.).

Connecting images and text. To learn the meaning of the images, we elevate the image representation to a semantic one, by connecting images and text. However, because our texts contain a lot of information not relevant to the image, our main method does not predict text from the image. The latter task has received sustained interest [67, 14, 30, 66, 48, 6, 12, 1, 16, 74] but our domain is unique in that articles that are paired with our images are orders of magnitude longer.

**Visual rhetoric.** Our work also belongs to a recent trend of developing algorithms to analyze visual media and the strategies that a media creator uses to convey a message. [31, 32] analyze the skills and characteristics that a politician is implied to have through a photo, e.g. "competent"; we adapt their method as a baseline in our setting. [49] study differences in facial portrayals between presidential candidates, and [70, 71] examine visual differences between supporters of the left or right. We learn to *generate* faces from the left and right. Further, we examine differences in general images rather than just faces. [26, 74] predict the persuasive messages of advertisements, but persuasion in political images is more subtle. These works are based on careful and expensive human annotations, while we aim to discover facets of bias in a weakly supervised way.

**Bias prediction in language.** Prior work in NLP has discovered indicators of biased language and political framing (i.e. presenting an event or person in a positive or negative light). For example, [54, 3] use carefully designed dictionary, lexical, grammatical and content features to detect biased language, using supervision over short phrases. Others [50, 9, 10, 11, 73, 68] have studied predicting politics from text. In contrast, it is not clear what "lexicon" of biased content to use for images.

#### 3 Dataset

Because no dataset exists for this problem, we assembled a large dataset of images and text about contemporary politically charged topics. We got a list of "biased" sources from mediabiasfactcheck.com which places news media on a spectrum from extreme left to extreme right. We used [47] to get a list of current "hot topics" e.g. immigration, LGBT rights, welfare, terrorism, the environment, etc. We crawled the media sources that were labeled left/right or extreme left/right for images using each of these topics as queries. After identifying images associated with each keyword and the pages they were on, we used [52] to extract articles. We obtained 1,861,336 images total and 1,559,004 articles total. We manually removed boilerplate text (headers, copyrights, etc.) which leaked into some articles.

#### 3.1 Data deduplication

Because sources cover the same events, some images are published multiple times. To prevent models from "cheating" by memorization, all experiments are performed on a "deduplicated" subset of our data. We extract features from a Resnet [24] model for all images. Because computing distances between all pairs is intractable, we use [39] for approximate kNN search (k=200). We set a threshold on neighbors' distances to find duplicates and near-duplicates. We determine the threshold empirically by examining hundreds of kNN matches to ensure all near-duplicates are detected. From each set of duplicates, we select one image (and its associated article) to remain in our "deduplicated" dataset while excluding all others. If the same image appeared in both left and right media sources, we keep it on the side where it was more common, e.g. one left source and three right sources would result in preserving one of the image-text pairs from the right sources. After removing duplicates, we are left with 1,079,588 unique images and paired text on which the remainder of this paper is based.



Figure 1: We asked workers to predict the political leaning of images. We show examples here where all annotators agree, the majority agree, and where there was no consensus.

#### 3.2 Crowdsourcing annotations

We treat the problem of predicting bias as a weakly supervised task. For training, we assume all image-text pairs have the political leaning of the source they come from. In Sec. 5.3 we show that this assumption is reasonable by leveraging human labels, though it is certainly not correct for all images / text, e.g. a left-leaning source may publish a right-leaning image to critique it. In order to better explore this assumption and understand human conceptions of bias, we ran a large-scale crowdsourcing study on Amazon Mechanical Turk (MTurk). We asked workers to guess the political leaning of images by indicating whether the image favored the left, right, or was unclear. In total, we showed 3,237 images to at least three workers each. We show examples of different levels of agreement in Fig. 1. In total, 993 were labeled with a clear L/R label by at least a majority. We also asked what image features were used to make their guess. The features workers could choose (and the count of each agreed upon) was: closeup-90 (closeup of specific person's face), known person-409 (portrays public figure in political way), multiple people-237 (group or class of people portrayed in political way), no people-81 (scenes or objects associated with parties, e.g. windmill/left, gun/right), symbols-104 (e.g. swastika, pride flag), non-photographic-130 (cartoons, charts, etc.), logos-77 (logo of e.g. CNN, FOX, etc.), and text in image-267 (e.g. text on protest signs, captions, etc.).

We also showed workers the image's article and asked a series of questions about the image-text pair, such as the political leaning of the *pair* (as opposed to image only), the topic (e.g. terrorism, LGBT) the pair is related to, and which article text best aligned with the image. We computed agreement scores and found that 2.45 out 3 annotators agreed on bias label on average, while 1.71 out of 3 agreed on topic, on average. Finally, we asked workers to provide a free-form text explanation of their politics prediction for a small number of images. We extracted semantic concepts from these explanations and later use them to train one of our baseline methods (Sec. 5.1). Humans often mentioned using the positive/negative portrayal of public figures and the gender, race and ethnicity of photo subjects. We provide a demonstration of differences in portrayal across L/R in Sec. 5.5. Absent these cues, workers used stereotypical notions of what issues the left/right discuss or their values. For example, for images of protests or college women, annotators might guess "left".

To ensure quality, we used validation images with obvious bias to disqualify careless workers. We restricted our task to US workers who passed a qualification test, had  $\geq 98\%$  approval rate, and who had completed  $\geq 1,000$  HITs. In total, we collected 14,327 sets of annotations (each containing image bias label, image-text pair bias label, topic, etc.) at a cost of \$4,771. We include a number of experimental results on this human annotated set of images in Sec. 5.3.

# 4 Approach

We hypothesize that the complementary textual domain provides a useful cue to guide the training of our visual bias classifier. The text of the articles includes words that clearly correlate with political bias, e.g. "unite", "medicaid", "donations", "homosexuality", "Putin", "Antifa" and "brutality" strongly correlate with left bias according to our model, while "defend", "retired", "NRA", "minister" and "cooperation" strongly correlate with right bias. By factoring out these semantic concepts into the auxiliary text domain, we enable our model to learn complementary visual cues. We use information flowing from the visual pipeline, and fuse it with the document embedding as an auxiliary source of information. Because we are primarily interested in *visual* political bias, we next remove our model's reliance on textual features, but keep all convolutional layers fixed. We train a linear bias classifier on top of the first model, using it as a feature extractor. Thus, at *test time*, our model predicts the bias of an image *without using any text*. We illustrate our method in Fig. 2.

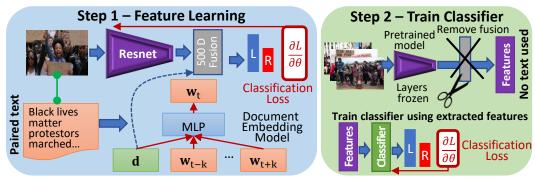


Figure 2: We propose a two-stage approach. In stage 1, we learn visual features jointly with paired text for bias classification. In stage 2, we remove the text dependency by training a classifier on top of our prior model using purely visual features. We show that this approach significantly outperforms directly training a model to predict bias. See Sec. 4.1 for details.

#### 4.1 Method details

We wish to capture the implicit semantics of an image by leveraging the association between images and text. More specifically, let  $\mathcal{D} = \{\mathbf{x}_i, \mathbf{a}_i, \mathbf{y}_i\}_{i=1}^N \tag{1}$ 

denote our dataset  $\mathcal{D}$ , where  $\mathbf{x}_i$  represents image i,  $\mathbf{a}_i$ , represents the textual article associated with the  $i^{th}$  image, and  $\mathbf{y}_i$  represents the political leaning of the image. In the first stage of our method, we seek the following function:

$$f_{\theta}\left(\mathbf{x}_{i}, \Omega\left(\mathbf{a}_{i}\right)\right) = \mathbf{y}_{i} \tag{2}$$

where  $\Omega$  (.) represents transforming the article text into a latent feature space. We train Doc2Vec [36] offline on our train set of articles to parameterize  $\Omega$ . Specifically,  $\Omega$  is trained to maximize the average log probability

$$\frac{1}{T} \sum_{t=1}^{T} \log p\left(\mathbf{w_t} | \mathbf{d}, \mathbf{w_{t-k}}, \dots, \mathbf{w_{t+k}}\right)$$
(3)

where T is the number of words in article  $\mathbf{a}$  (we omit the index i to simplify notation), p represents the probability of the indicated word,  $\mathbf{w_t}$  is the learned embedding for word t of article  $\mathbf{a}$ ,  $\mathbf{d}$  is the learned document embedding of  $\mathbf{a}$  (200D), and k is the window around the word to look when training the model. We use hierarchical softmax [42] to compute p. We train Doc2Vec on our corpus of news articles, and observe more intuitive embeddings than from a pretrained model.

After training, we compute  $\Omega$  for a given article a by finding the embedding d that maximizes Eq. 3.  $\Omega$  thus projects each article into a space where the resulting vector captures the overall latent context and topic of the article. We provide  $\Omega$  (a) to our model's fusion layer for each train image. The fusion layer is a linear layer which receives concatenated image and text features and learns to project them into a multimodal image-text embedding space which is finally used by the classifier.

The formulation of  $f_{\theta}(.)$  described above requires that the *ground-truth* text be available at test time and also does not ensure that our model is learning *visual* bias (i.e. the classifier may be relying primarily on text features and ignoring the visual channel completely). To address this problem, in the second stage of our method, we finetune  $f_{\theta}$  to directly predict the politics of an *image only*, without the text, as follows:  $f'_{\theta,\theta'}(\mathbf{x}_i) = \mathbf{y}_i$ . Specifically, we freeze the trained convolutional parameters of  $f_{\theta}$  and add a final linear classifier layer to the network, whose parameters are denoted  $\theta'$ . Because  $f_{\theta}$ 's convolutional layers have already been trained jointly with text features, they have already learned to extract visual features which complemented the text domain; we now learn to use those features *alone* for bias prediction, as shown in Fig. 2.

#### 4.2 Implementation details

All methods use the Resnet-50 [24] architecture and are initialized with a pretrained Imagenet model. We train all models using Adam [34], with learning rate of 1.0e-4 and minibatch size of 64 images. We use cross-entropy loss and apply class-weight balancing to correct for slight data imbalance between L/R. We use an image size of 224x224 and random horizontal flipping as data augmentation. We use Xavier initialization [21] for non-pretrained layers. We use PyTorch [46] to train all image

models. For our text embedding, we use [55], with  $\mathbf{d} \in \mathcal{R}^{200 \times 1}$  and train using distributed memory [36] for 20 epochs with window size k = 20, ignoring words which appear less than 20 times.

# 5 Experiments

In this section, we demonstrate our method's performance at predicting left/right bias. We show results on a large held-out test set from our dataset, whose left/right labels come from the leaning of the news source containing the image. We also show results on test images for which a majority of human annotators agreed on the bias and show how humans reason about visual bias. We show that seeing the complementary text information helped *humans* become more accurate at this task, much like seeing the text at training time helps our algorithm. We also show the challenge of our task through across-class nearest-neighbors, how the portrayal of politicians differs from the left to the right, images that best match various words from articles, and visualize how our model makes decisions about visual bias. Our supp. contains additional results such as results per-media source / per-political issue, an exploration of the learned text embedding space, failure cases for machines/humans, humans' reasoning behind their bias decisions, and examples from our dataset.

#### 5.1 Methods compared

For quantitative results, we show the accuracy of each method on predicting left/right bias. We compare against the following baselines:

- RESNET [24] A standard 50-layer classification Resnet.
- Joo [31] Adaptation of Joo et al.'s method for our task. We use [31]'s dataset to train predictors
  for 15 attributes and nine "intents" (qualities the photo subject is estimated to have, e.g. trustworthiness, competence). We then use the predictions for these attributes and intents on images from
  our dataset as additional features to a Resnet to predict a left/right leaning.
- HUMAN CONCEPTS We use the manually extracted vocabulary of bias-related concepts (e.g. "confederate", "African-American") from the human-provided explanations (Sec. 3.2) and download data for each from Google Image Search. We train a separate Resnet to predict concepts, and use it on each image in our dataset:  $p(c_j|\mathbf{x}_i)$  denotes the probability that image  $\mathbf{x}_i$  exhibits concept  $c_j$ . We then use the confidence of each detected concept, as a feature vector to predict bias.
- OCR We use [41] to recognize free-form scene text in images. Because images contain words not found in the default lexicon (e.g. Manafort), we create our own lexicon from the 100k most common words in our articles. We use [19] for spelling correction. We represent each recognized word as its learned word embedding, denoted  $\mathbf{w}'_i$ , weighed by the confidence of the recognition  $p(\mathbf{w}'_i)$  as provided by the recognition model. The feature is thus given by  $\frac{1}{n} \sum_{i=1}^{n} p(\mathbf{w}'_i) \mathbf{w}'_i$ .

All methods use the same residual network architecture. For methods relying on additional features, we use the fusion architecture in Fig. 2. For reference, we also show an upper-bound method OURS (GT) which uses the Ground Truth text paired with the images *at test time* (to compute a document embedding), in addition to the image. We thus consider it an upper-bound to the task of visual only prediction. OURS (GT) is the same as the first stage of our approach (see Fig. 2, left), without the addition of the image classifier layer in step 2.

#### 5.2 Evaluating on weakly supervised labels

In Table 1, we show the results of evaluating our methods on 75,148 held-out images with weakly supervised labels. Our method performs best overall. The top two performing methods rely on semantics discovered in the text domain (OURS and OCR). OCR is unique in that it is able to explicitly use text information at test time, by discovering text within the image and then using word embeddings. OURS improves over OCR by 2.6% (relative 3.8%, reduction in error of 8%). The improvement of OURS over RESNET is 3.4% (relative 5%, error reduction of 11%). This amounts to classifying an additional ~2,555 images correctly. Relying on the concepts humans identified actually slightly *hurt* performance compared to RESNET. This may be because of a disconnect between humans' preconceived notions about L/R and those required by the dataset. We finally observe Joo performs the weakest, likely because [31]'s data mainly features closeups of politicians, while ours contains a much broader image range.

Method	RESNET	Joo	HUMAN CONCEPTS	OCR	OURS	OURS (GT)
Accuracy	0.678	0.670	0.675	0.686	0.712	0.803

Table 1: Accuracy on weakly supervised labels with the best visual-only prediction method in bold.

Feature/Method	RESNET	Joo	HUMAN CONCEPTS	OCR	OURS	OURS (GT)
Closeup	0.567	0.544	0.622	0.578	0.656	0.578
Known Person	0.567	0.550	0.570	0.560	0.521	0.575
Multiple People	0.722	0.671	0.688	0.730	0.768	0.705
No People	0.556	0.605	0.494	0.580	0.593	0.667
Symbols	0.558	0.596	0.548	0.577	0.606	0.587
Non-Photographic	0.577	0.569	0.584	0.577	0.585	0.654
Logos	0.545	0.584	0.597	0.662	0.623	0.584
Text in Image	0.629	0.625	0.596	0.637	0.607	0.659
Average	0.590	0.593	0.587	0.613	0.620	0.626

Table 2: Accuracy on human consensus labels with the best visual-only prediction method in bold.

#### **5.3** Evaluating on human labels

We next tested our methods on test images which at least a majority of MTurkers labeled as having the same bias, i.e. those that humans agreed had a particular label. We describe this dataset in Sec. 3.2. Because workers also labeled images with what features of the image they used to make their prediction, we also break down each method's performance by feature. We show this result in Table 2. OURS performs best on average across all categories and performs best on four out of eight categories. Categories where OURS is outperformed on are reasonable: OCR performs best when text can be relied on in the image, i.e. "logos" and "text in image". We note that while the overall result for OCR approaches OURS, OURS works better on a broader set of images than OCR and is thus a more general method for predicting visual bias. OURS is also outperformed by HUMAN CONCEPTS when humans relied on a known face (politician, celebrity, etc.). This may be because HUMAN CONCEPTS relies on external training data (Sec. 5.1) which feature many known individuals, e.g. "rappers" and "founding fathers". JOO outperforms our method when the prediction depends on scene context ("no people"), again likely because Joo uses an external human-labeled dataset to learn features, including scene attributes (e.g. indoor, background, national flag, etc.). We note OURS (GT) performs sig, worse on human labels vs. weakly-supervised labels. This is likely because OURS (GT) has learned to exploit dataset-specific features (e.g. author names, header text, etc.) for prediction, which does not actually translate into humans' commonsense understanding of political bias.

We next test whether our assumption that all images harvested from a right- or left-leaning source exhibit that type of bias is reasonable. Several results computed from our ground-truth human study suggest that our web labels are a reasonable approximation of bias. First, we observe that the relative performance of the methods across Table 1 and 2 is roughly maintained; OURS is best, followed by OCR, and the other methods essentially tied. The results are also sound, e.g. when humans used text, OCR tends to do better, which indicates the model's concept of bias correlates with humans'.

We also performed two other experiments to verify our conclusions. First, we explored the difference between the performance of our method on images on which the *majority* of humans agreed vs. those on which humans *unanimously* agreed. We found that our method worked better when humans unanimously labeled the images vs. simple majority (gain of 4.4%). This suggests that as humans become more certain of bias, our model (trained on noisy data) also performs better. Next, we evaluated the impact of text on humans' bias predictions. We compared how humans *changed* their predictions (made originally using the image only) after they saw the text paired with the image. We found that when workers picked a L/R label, the label was strongly correlated with the weakly supervised label. Moreover, after seeing the text, humans became even more correct with respect to the noisy labels, switching many "unclear" predictions to the "correct" label (i.e. the noisy label). This indicates that: 1) our noisy labels are a good approximation of the true bias of the images; and 2) the paired text is useful for predicting bias (a result also borne out by our experiments).

#### 5.4 Quantitative ablations

In order to test the soundness of our method and our experimental design, we performed several ablations. We first tested the importance of the second stage of our method (right side of Fig. 2). To do so, we used OURS (GT), the result of the first stage of our method and instead of performing

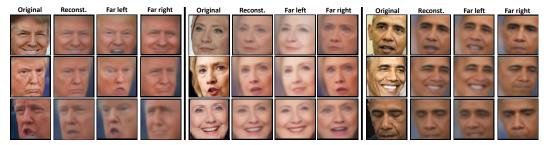


Figure 3: We modified photos to be more left/right. We show the model's "reconstruction" of each face next to the original sample, followed by the sample transformed to the far left and right.



Figure 4: For a set of topics (e.g. LGBT, climate change), we show the closest pair of images across the left/right divide. In each pair, the image on the left is from a left-leaning source, and the one on the right is from a right-leaning source. Note how similar the images in each pair are on the surface.

stage 2, we removed the dependency on text by zeroing out all text embedding weights in the fusion layer. We evaluated on our weakly supervised test set and obtained 0.677, a result sig. worse than our full method, underscoring the importance of stage 2. We next tested how the performance of our method varied given the length of the article text. We thus trained our method with the first k sentences of the article and obtained these results:  $k = 1 \rightarrow 0.672, k = 2 \rightarrow 0.669, k = 5 \rightarrow 0.668, k = 10 \rightarrow 0.669$ . All choices of k tested performed sig. worse than using the full article (0.712).

We finally examined how reliant our method was on images from a particular media source being in our train set (i.e. to test if the model was learning non-generalizable, source-specific features). We experimented with leaving out all training data harvested from a few popular sources. The result was (before excluding  $\rightarrow$  after excluding): Breitbart (0.607 $\rightarrow$ 0.566), CNN (0.873 $\rightarrow$ 0.866), CommonDreams (0.647 $\rightarrow$ 0.636), DailyCaller (0.703 $\rightarrow$ 0.667), DemocraticUnderground (0.713 $\rightarrow$ 0.700), NewsMax (0.685 $\rightarrow$ 0.628), and TheBlaze (0.746 $\rightarrow$ 0.742). We observed only a slight decrease for all sources we tested, suggesting our method is not dependent on seeing the source at train time.

#### 5.5 Qualitative results

Modeling facial differences across politics: Many workers noted how politicians were portrayed in making their decision (Sec. 3.2). To visualize the differences in how well-known individuals are portrayed within our dataset, we trained a generative model to modify a given Trump/Clinton/Obama face, and make it appear as if it came from a left/right leaning source. We use a variation of the autoencoder-based model from [64], which learns a distribution of facial attributes and latent features on ads, not political images. We train the model using the features from the original method on faces of Trump/Clinton/Obama detected in our dataset using [33]. We use [59] for face recognition. To modify an image, we condition the generator on the image's embedding and modify the distribution of attributes/expressions for the image to match that person's average portrayal on the left/right, following [64]'s technique. We show the results in Fig. 3. Observe that Trump and Clinton appear angry on the far-left/right (respectively) end of the spectrum. In contrast, all three appear happy/benevolent in sources supporting their own party. We also observe Clinton appears younger in far-left sources. In far-right sources, Obama appears confused or embarrassed. These results further underscore that our weakly supervised labels are accurate enough to extract a meaningful signal.

**Nearest neighbors across issues and politics:** In Fig. 4, we show the challenge of classifying in visual space only. We compute the distance between images from the left and right, and show L/R pairs that have a small distance in feature space within topics. For BLM, the left image is serious, while the right image is whimsical. For climate change, one presents a more negative vision, while the other is picturesque. Both border control images show fire, but the left one is of a Trump effigy. For terrorism, the left image shows a white domestic terrorist while the right shows Middle-Eastern men. These pairs highlight how subtle the distinctions between L/R are for some images.



Figure 5: We train a model to predict words from images. The model learns relevant visual cues for each word, demonstrating the utility of exploiting text, even for purely visual classification.



Figure 6: We show visual explanations using [5]. We note that our model looks to logos and faces of public figures, while the baseline uses objects (e.g. mic.) and scene type (e.g. city in background).

Visualizing image-text alignment: We wanted to see how well our model could align images and concepts from text. We formulated a variation of our method which, instead of predicting bias, predicted relevant words. We chose a set of 1k words that had the lowest average distance between their images' features (i.e. were visually consistent on avg.) from the 10k most frequent words. The model is trained to predict whether each word is/is not present in the image's article given the image and text embedding. In Fig. 5, we show examples of images that were among the top-100 strongest predictions for that word. We see that the model strongly predicts "antifa" for black-clad protestors, "brutality" for police scenes and protests, "immigrant" for the border wall and Hispanics, and "LGBT" for pride flags. Though the image may only relate to a small portion of the lengthy text, there is enough visual signal present for the model to learn, demonstrating the benefit of leveraging text to complement the model's training.

**Visual explanations:** We wanted to see whether we could interpret how our model learned to perform bias classification. We used Grad-CAM++ [5] to compute attention maps on images that humans annotated. We show the result in Fig. 6. We observe that our model pays the most attention to logos and faces of public figures. We see the model only focuses on the "PBS" logo in the first row (and ignores the face of the lesser known person), but pays attention to both the "Fox News" logo and the face of the well-known commentator in the second row. We believe that because our model was trained with the topic information provided via the text embedding during stage one, the visual component of the model learned to focus on learning visual features that complemented the text (such as logos and faces). Ultimately these features work better even without the text.

#### 6 Conclusion

We assembled a large dataset of biased images and paired articles and presented a weakly supervised approach for inferring the political bias of images. Our method leverages the image's paired text to guide the model's training process towards relevant semantics in a way which ultimately improves bias classification. We demonstrate the contribution of our method and dataset both quantitatively and qualitatively, including on a large crowdsourced dataset. Use cases of our work include: inferring the bias of new media sources, constructing balanced "news feeds," or detecting political ads. Broadly speaking, our method demonstrates the potential of using an auxiliary semantic space, e.g. for abstract tasks such as video summarization and visual commonsense reasoning.

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# References

- [1] P. Anderson, X. He, C. Buehler, D. Teney, M. Johnson, S. Gould, and L. Zhang. Bottom-up and top-down attention for image captioning and visual question answering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.
- [2] M. C. Angermeyer and B. Schulze. Reinforcing stereotypes: how the focus on forensic cases in news reporting may influence public attitudes towards the mentally ill. *International Journal of Law and Psychiatry*, 2001.
- [3] E. Baumer, E. Elovic, Y. Qin, F. Polletta, and G. Gay. Testing and comparing computational approaches for identifying the language of framing in political news. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1472–1482, 2015.
- [4] G. Borghi, S. Pini, F. Grazioli, R. Vezzani, and R. Cucchiara. Face verification from depth using privileged information. In *British Machine Vision Conference (BMVC)*. Springer, 2018.
- [5] A. Chattopadhay, A. Sarkar, P. Howlader, and V. N. Balasubramanian. Grad-cam++: Generalized gradient-based visual explanations for deep convolutional networks. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), pages 839–847. IEEE, 2018.
- [6] T.-H. Chen, Y.-H. Liao, C.-Y. Chuang, W.-T. Hsu, J. Fu, and M. Sun. Show, adapt and tell: Adversarial training of cross-domain image captioner. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.
- [7] X. Chen and A. Gupta. Webly supervised learning of convolutional networks. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pages 1431–1439, 2015.
- [8] R. G. Cinbis, J. Verbeek, and C. Schmid. Weakly supervised object localization with multi-fold multiple instance learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI)*, 39(1):189–203, 2016.
- [9] R. Cohen and D. Ruths. Classifying political orientation on twitter: It's not easy! In Seventh International Association for the Advancement of Artificial Intelligence (AAAI) Conference on Weblogs and Social Media, 2013
- [10] E. Colleoni, A. Rozza, and A. Arvidsson. Echo chamber or public sphere? predicting political orientation and measuring political homophily in twitter using big data. *Journal of communication*, 64(2):317–332, 2014
- [11] M. D. Conover, B. Gonçalves, J. Ratkiewicz, A. Flammini, and F. Menczer. Predicting the political alignment of twitter users. In *IEEE Third International Conference on Privacy, Security, Risk and Trust* (PASSAT) and IEEE Third International Conference on Social Computing (SocialCom), pages 192–199. IEEE, 2011.
- [12] B. Dai, S. Fidler, R. Urtasun, and D. Lin. Towards diverse and natural image descriptions via a conditional gan. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 2017.
- [13] C. Doersch, S. Singh, A. Gupta, J. Sivic, and A. Efros. What makes paris look like paris? ACM Transactions on Graphics, 31(4), 2012.
- [14] J. Donahue, L. Anne Hendricks, S. Guadarrama, M. Rohrbach, S. Venugopalan, K. Saenko, and T. Darrell. Long-term recurrent convolutional networks for visual recognition and description. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2015.
- [15] T. B. Edsall. Studies: Conservatives are from mars, liberals are from venus, February 2012. https://www.theatlantic.com/politics/archive/2012/02/studies-conservatives-are-from-mars-liberals-are-from-venus/252416/.
- [16] A. Eisenschtat and L. Wolf. Linking image and text with 2-way nets. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017.
- [17] D. Elliott and Á. Kádár. Imagination improves multimodal translation. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 130–141, 2017.
- [18] L. Fei-Fei and P. Perona. A bayesian hierarchical model for learning natural scene categories. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, volume 2, pages 524–531. IEEE, 2005.
- [19] W. Garbe. Symspell. https://github.com/wolfgarbe/SymSpell.
- [20] M. Gilens. Race and poverty in americapublic misperceptions and the american news media. *Public Opinion Quarterly*, 60(4):515–541, 1996.
- [21] X. Glorot and Y. Bengio. Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics (AISTATS)*, pages 249–256, 2010.
- [22] L. Gomez, Y. Patel, M. Rusinol, D. Karatzas, and C. V. Jawahar. Self-supervised learning of visual features through embedding images into text topic spaces. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017.

- [23] C. Happer and G. Philo. The role of the media in the construction of public belief and social change. *Journal of Social and Political Psychology*, 1(1):321–336, 2013.
- [24] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016.
- [25] J. Hoffman, S. Gupta, and T. Darrell. Learning with side information through modality hallucination. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 826–834. IEEE, 2016.
- [26] Z. Hussain, M. Zhang, X. Zhang, K. Ye, C. Thomas, Z. Agha, N. Ong, and A. Kovashka. Automatic understanding of image and video advertisements. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.
- [27] Y. Jae Lee, A. A. Efros, and M. Hebert. Style-aware mid-level representation for discovering visual connections in space and time. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pages 1857–1864, 2013.
- [28] L. Jiang, D. Meng, Q. Zhao, S. Shan, and A. G. Hauptmann. Self-paced curriculum learning. In *Twenty-Ninth Association for the Advancement of Artificial Intelligence (AAAI) Conference on Artificial Intelligence*, volume 2, page 6, 2015.
- [29] L. Jiang, Z. Zhou, T. Leung, L.-J. Li, and L. Fei-Fei. Mentornet: Learning data-driven curriculum for very deep neural networks on corrupted labels. In *Proceedings of the International Conference on Machine Learning (ICML)*, pages 2309–2318, 2018.
- [30] J. Johnson, A. Karpathy, and L. Fei-Fei. Densecap: Fully convolutional localization networks for dense captioning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.
- [31] J. Joo, W. Li, F. F. Steen, and S.-C. Zhu. Visual persuasion: Inferring communicative intents of images. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014.
- [32] J. Joo, F. F. Steen, and S.-C. Zhu. Automated facial trait judgment and election outcome prediction: Social dimensions of face. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 2015.
- [33] D. E. King. Dlib-ml: A machine learning toolkit. *Journal of Machine Learning Research*, 10:1755–1758, 2009.
- [34] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. *Proceedings of the International Conference on Learning Representations (ICLR)*, 2015.
- [35] J. Lambert, O. Sener, and S. Savarese. Deep learning under privileged information using heteroscedastic dropout. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2018.
- [36] Q. Le and T. Mikolov. Distributed representations of sentences and documents. In *Proceedings of the International Conference on Machine Learning (ICML)*, pages 1188–1196, 2014.
- [37] H. Li, J. G. Ellis, L. Zhang, and S.-F. Chang. Patternnet: Visual pattern mining with deep neural network. In Proceedings of the 2018 ACM on International Conference on Multimedia Retrieval, pages 291–299. ACM, 2018.
- [38] Y. Li, L. Liu, C. Shen, and A. Van Den Hengel. Mining mid-level visual patterns with deep cnn activations. *International Journal of Computer Vision (IJCV)*, 121(3):344–364, 2017.
- [39] Y. A. Malkov and D. A. Yashunin. Efficient and robust approximate nearest neighbor search using hierarchical navigable small world graphs. *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI)*, 2016.
- [40] J. B. Merrill. Liberal, moderate or conservative? see how facebook labels you. *The New York Times*, Aug 2016.
- [41] B. S. Minghui Liao and X. Bai. TextBoxes++: A single-shot oriented scene text detector. *IEEE Transactions on Image Processing*, 27(8):3676–3690, 2018.
- [42] F. Morin and Y. Bengio. Hierarchical probabilistic neural network language model. In *Tenth International Workshop on Artificial Intelligence and Statistics (AISTATS)*, volume 5, pages 246–252. Citeseer, 2005.
- [43] S. Motiian, M. Piccirilli, D. A. Adjeroh, and G. Doretto. Information bottleneck learning using privileged information for visual recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1496–1505. IEEE, 2016.
- [44] C. L. Muñoz and T. L. Towner. The image is the message: Instagram marketing and the 2016 presidential primary season. *Journal of Political Marketing*, 16(3-4):290–318, 2017.
- [45] M. Oquab, L. Bottou, I. Laptev, and J. Sivic. Is object localization for free?-weakly-supervised learning with convolutional neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 685–694, 2015.
- [46] A. Paszke, S. Gross, S. Chintala, G. Chanan, E. Yang, Z. DeVito, Z. Lin, A. Desmaison, L. Antiga, and A. Lerer. Automatic differentiation in pytorch. In *Advances in Neural Information Processing Systems Workshops (NIPS-W)*, 2017.
- [47] T. Peck and N. Boutelier. Big political data. https://www.isidewith.com/polls. Accessed 2018.

- [48] M. Pedersoli, T. Lucas, C. Schmid, and J. Verbeek. Areas of attention for image captioning. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.
- [49] Y. Peng. Same candidates, different faces: Uncovering media bias in visual portrayals of presidential candidates with computer vision. *Journal of Communication*, 68(5):920–941, 2018.
- [50] M. Pennacchiotti and A.-M. Popescu. A machine learning approach to twitter user classification. In Fifth International Association for the Advancement of Artificial Intelligence (AAAI) Conference on Weblogs and Social Media, 2011.
- [51] A. Pentina, V. Sharmanska, and C. H. Lampert. Curriculum learning of multiple tasks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 5492–5500, 2015.
- [52] M. E. Peters and D. Lecocq. Content extraction using diverse feature sets. In Proceedings of the 22nd International Conference on World Wide Web (WWW), pages 89–90. ACM, 2013.
- [53] G. Philo. Active audiences and the construction of public knowledge. *Journalism Studies*, 9(4):535–544, 2008
- [54] M. Recasens, C. Danescu-Niculescu-Mizil, and D. Jurafsky. Linguistic models for analyzing and detecting biased language. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, pages 1650–1659, 2013.
- [55] R. Řehůřek and P. Sojka. Software Framework for Topic Modelling with Large Corpora. In Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks, pages 45–50, Valletta, Malta, May 2010. ELRA. http://is.muni.cz/publication/884893/en.
- [56] A. Richard, H. Kuehne, and J. Gall. Weakly supervised action learning with rnn based fine-to-coarse modeling. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 754–763, 2017.
- [57] D. Schill. The visual image and the political image: A review of visual communication research in the field of political communication. *Review of Communication*, 12(2):118–142, 2012.
- [58] D. Schreiber, G. Fonzo, A. N. Simmons, C. T. Dawes, T. Flagan, J. H. Fowler, and M. P. Paulus. Red brain, blue brain: Evaluative processes differ in democrats and republicans. *PLOS ONE*, 8(2):1–6, 02 2013.
- [59] F. Schroff, D. Kalenichenko, and J. Philbin. Facenet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 815–823, 2015.
- [60] V. Sharmanska, N. Quadrianto, and C. H. Lampert. Learning to rank using privileged information. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 825–832. IEEE, 2013.
- [61] R. Sicre, Y. S. Avrithis, E. Kijak, and F. Jurie. Unsupervised part learning for visual recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 3116–3124, 2017.
- [62] S. Singh, A. Gupta, and A. A. Efros. Unsupervised discovery of mid-level discriminative patches. In Proceedings of the European Conference on Computer Vision (ECCV), pages 73–86. Springer, 2012.
- [63] J. Sivic, B. C. Russell, A. A. Efros, A. Zisserman, and W. T. Freeman. Discovering objects and their location in images. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, volume 1, pages 370–377. IEEE, 2005.
- [64] C. Thomas and A. Kovashka. Persuasive faces: Generating faces in advertisements. In *Proceedings of the British Machine Vision Conference (BMVC)*, 2018.
- [65] V. Vapnik and R. Izmailov. Learning using privileged information: similarity control and knowledge transfer. *Journal of Machine Learning Research (JMLR)*, 16(2023-2049):2, 2015.
- [66] S. Venugopalan, L. Anne Hendricks, M. Rohrbach, R. Mooney, T. Darrell, and K. Saenko. Captioning images with diverse objects. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.
- [67] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan. Show and tell: A neural image caption generator. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 3156–3164, 2015.
- [68] S. Volkova, G. Coppersmith, and B. Van Durme. Inferring user political preferences from streaming communications. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, volume 1, pages 186–196, 2014.
- [69] L. Wang, Y. Xiong, D. Lin, and L. Van Gool. Untrimmednets for weakly supervised action recognition and detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4325–4334, 2017.
- [70] Y. Wang, Y. Feng, Z. Hong, R. Berger, and J. Luo. How polarized have we become? a multimodal classification of trump followers and clinton followers. In *International Conference on Social Informatics*, 2017
- [71] Y. Wang, Y. Li, and J. Luo. Deciphering the 2016 us presidential campaign in the twitter sphere: A comparison of the trumpists and clintonists. In *Tenth International Association for the Advancement of Artificial Intelligence (AAAI) Conference on Web and Social Media*, pages 723–726, 2016.

- [72] Y. Wei, Z. Shen, B. Cheng, H. Shi, J. Xiong, J. Feng, and T. Huang. Ts2c: Tight box mining with surrounding segmentation context for weakly supervised object detection. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 434–450, 2018.
- [73] F. M. F. Wong, C. W. Tan, S. Sen, and M. Chiang. Quantifying political leaning from tweets, retweets, and retweeters. *IEEE Transactions on Knowledge and Data Engineering*, 28(8):2158–2172, 2016.
- [74] K. Ye, N. Honarvar Nazari, J. Hahn, Z. Hussain, M. Zhang, and A. Kovashka. Interpreting the rhetoric of visual advertisements. *To appear, IEEE Transactions on Pattern Analysis and Machine Intelligence* (PAMI), 2019.
- [75] K. Ye, M. Zhang, A. Kovashka, W. Li, D. Qin, and J. Berent. Cap2det: Learning to amplify weak caption supervision for object detection. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, Oct 2019.
- [76] A. R. Zamir, T.-L. Wu, L. Sun, W. B. Shen, B. E. Shi, J. Malik, and S. Savarese. Feedback networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1808–1817. IEEE, 2017.
- [77] Y. Zhang, P. David, and B. Gong. Curriculum domain adaptation for semantic segmentation of urban scenes. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, pages 2020–2030, 2017.
- [78] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba. Learning deep features for discriminative localization. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2921–2929, 2016.
- [79] F. Zhou, F. De la Torre, and J. F. Cohn. Unsupervised discovery of facial events. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2574–2581. IEEE, 2010.

# Predicting the Politics of an Image Using Webly Supervised Data (Supplementary Material)

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# 1 Introduction

This document presents supplementary results to our main text. We first present additional details of our new political bias dataset, in Section 2. Next, in Section 3, we provide two additional quantitative results using our test set which shows the differences between our best performing method and the baselines on the various topics within our dataset. We also provide results for an application of predicting the bias of different media sources. In Section 4, we present additional qualitative results to complement our result in Fig. 5 from the main text, i.e. images that most strongly predicted several words from articles. In Section 5, we illustrate what our trained document embedding model learns by showing nearby words for a number of query words. In Section 6, we compare human vs. machine performance by showing images that either our best algorithm or humans failed to classify (or both). In Section 7, we include additional examples of images agreed upon by human annotators, as well as the free-form text reasons our participants gave for their Left / Right guesses. We also include our MTurk data collection interface. Finally, in Section 8, we show example images and articles from our dataset.

#### 2 Dataset Details

In this section, we present additional details of our new political bias dataset to complement our main text. Our dataset contains 1,861,336 images total and 1,559,004 articles total. However, after our deduplication procedure (described in our main text), we are left with 1,079,588 unique images upon which we conduct all experiments. In this section, we break down this *unique* count by politics, topic, and media source. We wish to re-emphasize that even though we exclude duplicates here, the articles associated with duplicate images are not necessarily duplicates (the overwhelming majority are unique). Thus, a large body of potentially useful image-text pairs are excluded from this description because the image associated with the text is not unique.

Figure 1 shows the breakdown of unique images in our dataset by politics. There are more images on the left than on the right, resulting in a slight class imbalance. We correct for this class imbalance during training for all of our experiments by ensuring equal class weight in the loss terms. Figure 2 further breaks down the distribution images by topic. For example, we see our dataset contains 83,145 unique images on the subject of religion (from both L/R), our most frequent category, while we collected 17,073 on the subject of vaccines, our least frequent category.

We also present the frequency distribution of our deduplicated dataset broken down by media source in the attached Microsoft Excel file media\_source\_stats.xlsx as there are too many to include or visualize in this document. Note that we also include the political leaning of the media source, as assigned by Media Bias Fact Check (see our main text for details).

#### **Dataset Counts by Politics (after deduplication)**

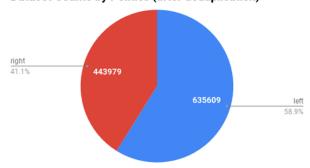


Figure 1: We illustrate the distribution of Left/Right unique images in our deduplicated dataset.

# Dataset Counts by Issue (after deduplication)

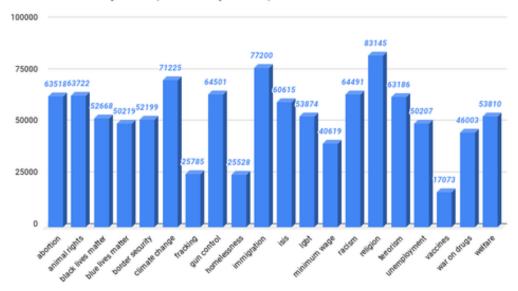


Figure 2: We show the distribution of unique images in our dataset by topic, across both Left/Right.

# 3 Quantitative Results

We present two quantitative results to supplement our main text. We first wanted to understand on what types of images our best performing method, OURS outperformed the RESNET baseline. In Table 1, we show a result which shows the top-3 topics that our method performed the best (and worst) over the baseline. We notice that for no topic does the baseline outperform our method. Even for those topics on which the baseline performs most competitively with our method, our method still outperforms it by 1-2%. We include complete results including additional baselines, for all topics in the included file, topic\_results.xlsx.

Method	Vaccines	Fracking	War on Drugs	Border Security	Black Lives Matter	Climate Change
RESNET	0.6768	0.6737	0.6684	0.6922	0.7026	0.6934
OURS	0.7422	0.7209	0.7128	0.7161	0.7269	0.7179

Table 1: Average performance for the three topics where our method achieves the largest vs smallest improvement over the baseline.

Method	Top-20	Top-100	Sun	Change	Breitbart	NewSt	NewYorker	NatRev	Slate	CNN	RevCom
RESNET	0.697	0.690	0.627	0.653	0.527	0.821	0.873	0.718	0.798	0.795	0.875
OURS	0.739	0.724	0.707	0.690	0.607	0.808	0.934	0.758	0.793	0.873	0.781

Table 2: Average performance for the top-20, and top-100 news sources, and individual results for some popular news sources.

In Table 2, we analyze the results as a function of the media source to which the image belongs. We compute the performance of our method on images exclusively from a particular media source, for each media source. We then rank the sources by number of samples in the test set, and check how performance changes as the number of samples decreases. We see that for media sources with more samples, OURS achieves a stronger result than the RESNET baseline (0.739 vs 0.697). We also show results for individual well-known media sources that have many samples in our dataset. The Sun, Breitbart, and National Review are well-known right-leaning sources, while the rest are left-leaning. Our method works well for both right- and left-leaning sources. For a few left-leaning sources, the baseline achieves stronger results. Among common sources, the baseline's gain is largest on RevCom, a *very* far-left, "revolutionary communism" website. It is surprising to see how accurate we can infer leaning from images alone; close to or over 80% for many sources shown.

We also provide supplementary results to complement this result in media\_source\_results.xlsx, including for other baselines. We break down the performance for each of our methods by media source. We observe that our method, OURS consistently outperforms the baselines, often substantially.

# 4 Image to Word Prediction Results

In our main text, we described a model trained to predict words from images. We trained this model to predict which words, from a fixed dictionary of the 1000 most visual words (see main text for details), would be in the article paired with the image. For this result only, we also conditioned the model on the document embedding of the article paired with the image. After training, we ran our entire large weakly-supervised test set through this model and predicted words for all images. For each word, we then sorted all test set images by the score the model assigned for the prediction of that word and show the 100 images for each that have the highest overall probability. We include results for several words in the image\_to\_word folder. We include results for several words, including "immigrant", "lgbt", "antifa", and "nationalist". We see that the images which strongly predicted the word "immigrant" often feature Hispanic people, children, or law enforcement symbols / personnel. For "lgbt", we notice that many images feature rainbow flags. "Antifa" often features street scenes with protestors wearing black. We also observe fascist symbols, such as swastikas or Nazi salutes in these photos. "Nationalist" features numerous examples of white supremacist imagery, including Ku Klux Klan garbs, swastikas, and Celtic crosses: symbolism associated with white supremacist and neo-nazi movements. Collectively these results indicate that, although the articles paired with the text are lengthly and much more weakly aligned than traditional image-text embedding tasks (i.e. captions, descriptions, etc.), a consistent visual signal exists that our model is able to grasp.

#### 5 Textual Embedding Word Retrieval Results

We trained a text embedding [1] model on articles from our dataset. In Table 3 we show an example of what our model learned for a number of query words. We compute the embedding of the query words using our model, then find the nearest words in embedding space from the learned dictionary and rank them. We observe that for "Donald Trump", several of the top words are in Spanish, which are likely coming from articles related to immigration concerning Trump. The translation of these words is fitting in this context, i.e. *intensa* means "intense", while "ultraderecha" means far-right. "Horripilantes" means "horrifying / terrifying." We also notice a "#" sign associated with Trump, likely coming from his use of Twitter. Importantly, we noticed for *events*, like Charlottesville (a protest event in which a protestor was run over by a car in a hate crime), relevant concepts that our *image* classifiers could potentially pick up on appear. For example, "riots", "antifa" (a protest group), "rally", etc. are all visualizable concepts associated with the event. We observe for another event, "Parkland" (a mass school shooting event involving 17 deaths), nearby concepts are "Newtown" (another school shooting), "Hogg" (a survivor of the Parkland shooting), "NRA" (the National Rifle Association, which opposed gun measures following the event and was the subject of significant

Query phrase:	donald trump	charlottesville	liberal	fascist	parkland	
	auxiliar: 0.4155	charleston: 0.7303	leftist: 0.2721	fascism: 0.7861	newtown: 0.7640	
	intensa: 0.4132	parkland: 0.7189	progressive: 0.2650	fascists: 0.7494	hogg: 0.7635	
	macron: 0.4102	antifa: 0.7135	conservative: 0.2583	nazi: 0.7169	stoneman: 0.7501	
	putin: 0.4042	kkk: 0.7117	liberals: 0.2541	racists: 0.7128	nra: 0.7455	
	ultraderecha: 0.4010	ferguson: 0.7038	much: 0.2516	racist: 0.7068	charlottesville: 0.7189	
	horripilantes: 0.4005	dallas: 0.6998	wing: 0.2516	totalitarian: 0.6903	shooting: 0.7161	
	billionaire: 0.3991	confederate: 0.6995	mainstream: 0.2514	repressive: 0.6866	walkout: 0.7135	
	pence: 0.3980	richmond: 0.6956	centrist: 0.2420	terrorist: 0.6862	walkouts: 0.7029	
	obama: 0.3937	shooting: 0.6879	moderate: 0.2323	filmado: 0.6791	charleston: 0.7002	
	cruz: 0.3928	horrific: 0.6844	emerged: 0.2312	imperialist: 0.6771	tragedy: 0.6991	
	duterte: 0.3924	portland: 0.6828	dismal: 0.2309	communist: 0.6729	orlando: 0.6986	
	erdogan: 0.3919	riots: 0.6826	steadily: 0.2269	nazis: 0.6666	emma4change: 0.6931	
	continuado: 0.3898	cleveland: 0.6817	radical: 0.2263	globalist: 0.6659	msd: 0.6844	
	mueller: 0.3876	heyer: 0.6806	portrayed: 0.2256	nationalist: 0.6655	sandyhook: 0.6841	
Results:	tonight: 0.3874	protest: 0.6782	conservatives: 0.2253	genocidal: 0.6630	shootings: 0.6795	
Resuits.	inauguration: 0.3869	rally: 0.6779	shifted: 0.2248	rogue: 0.6627	gun: 0.6752	
	gop: 0.3852	nfl: 0.6760	defeaning: 0.2245	authoritarian: 0.6620	marjory: 0.6739	
	america: 0.3848	tragedy: 0.6757	plummeted: 0.2244	extremist: 0.6603	senseless: 0.6701	
	potus: 0.3835	islamophobia: 0.6727	outflanked: 0.2219	vanguard: 0.6599	kasky: 0.6688	
	brexit: 0.3834	anticom: 0.6721	progressives: 0.2218	antifascist: 0.6583	neveragain: 0.6665	
	presidency: 0.3819	spike: 0.6719	leftwing: 0.2217	avakian: 0.6579	trayvon: 0.6654	
	alabama: 0.3817	berkeley: 0.6718	touted: 0.2209	aholes: 0.6571	7to: 0.6644	
	marcharse: 0.3814	counterprotesters: 0.6702	democrat: 0.2209	waok: 0.6566	sarasota: 0.6613	
	cabinet: 0.3812	barcelona: 0.6692	12,030: 0.2204	troutdale: 0.6565	columbine: 0.6610	
	netanyahu: 0.3779	memphis: 0.6679	long: 0.2196	clown: 0.6564	horrific: 0.6597	
	milo: 0.3770	heaphy: 0.6669	corporatists: 0.2194	supremacist: 0.6556	gaskill: 0.6596	
	republicans: 0.3766	alt: 0.6665	served: 0.2186	democrat: 0.6548	manjarres: 0.6596	
	opioid: 0.3757	weekend: 0.6662	framed: 0.2186	supremacy: 0.6548	florida: 0.6583	
	comey: 0.3737	mcauliffe: 0.6657	hardline: 0.2182	lunatic: 0.6545	loesch: 0.6576	
	#: 0.3736	spencer: 0.6654	leftward: 0.2176	misogynist: 0.6533	nationalwalkoutday: 0.6574	

Table 3: We show examples of our learned text embedding. At the top, we show several "query phrases" which we embed using our method. We then compute the distance from each query phrase to all other learned words in our dataset's vocabulary and rank the words in order of increasing distance. Thus, retrieved words near the top are more closely related to the query phrase in the learned space than words below.

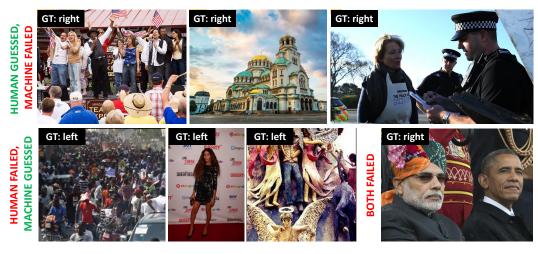


Figure 3: Images that either our best algorithm failed to classify (top), humans failed (bottom left) or both human and machine failed (bottom right). Please see text for our explanation.

press), and a variety of other hashtags and concepts associated with the event. We believe that these results illustrate *how* leveraging text helps our method ultimately perform better by forcing our classifiers to learn to pay attention to certain visual concepts, after being conditioned on the latent document embedding at training time. The representation our image classifiers learn guided by this latent, weak supervision ultimately proves to be superior to the other approaches we tested. We include many additional word query results in learned\_word\_embeddings.xlsx.

# 6 Human vs. Machine Abilities

In Fig. 3, we show images that humans and/or our best-performing algorithm (OURS) were able/unable to classify. At the top, we show the gap between human reasoning abilities and our classifier. The first image at the top has a subtle country vibe (associated with the right), which was imperceptible

for our algorithm. Next is an image of a non-western church, which was likely too different from churches in the training set. The third image shows British actress Emma Thompson campaigning for Greenpeace and getting cited; our algorithm is unable to analyze such complex scenes. At the bottom left of the figure, we show images that humans were unable to classify, but bias in the data helped our algorithm classify. Images of protests, Hollywood, and art, are common in left-leaning images. Finally, we show an image that neither human nor algorithm were able to classify, as it depends on context from the article, which is unavailable at test time.

# 7 MTurk Responses

In Figures 4-6, we show example images which at least a majority (2/3) of humans were able to guess the politics of correctly. We note that many times, when a politician of a particular party is shown, human annotators assume the image is the same leaning as the politician's party (e.g. image of Trump is right). Annotators often rely on racial stereotypes as well ("black women are more liberal," "most rappers are left," "left muslims", "older white man" is right-leaning). Relying on these stereotypical concepts in our HUMAN CONCEPTS model explains why that model performs best on those images containing humans (see main text), though it doesn't perform best in the dataset at large. We also observe that humans tend to associate the right with guns, patriotic symbols, and religion, whereas they tend to associate peace, compassion, diversity, protests, and minorities with the left. Humans also recognized some of the people appearing in the images and relied on their external knowledge of that person's political leanings to guess the image's label. We also include a complete listing of the concepts that were extracted from the MTurk free-form text explanations in human\_concepts.xlsx.

We also include our MTurk data collection interface in HTML file MTurk\_Inferface.html. Note that as you answer the questions, additional questions will appear. We first asked annotators to determine if the image met certain exclusionary criteria, i.e. text, blurry, etc. We then asked annotators to classify the image as left / right / ambiguous. We then asked what features of the image were relied on by the annotator to make their decision. We then showed annotators the article text going with the document and asked whether the text met certain exclusionary criteria, mainly originating from HTML scraping errors. We also asked annotators if the image and text were related to one another and to paste the text from the article that most aligned with the image. We then asked the workers to predict the politics of the image-text pair (as opposed to the image alone) and finally asked workers to state political topic(s) of the image-text pair.

# 8 Example Images and Documents from Dataset

In Figures 7-9, we show example images and some text from their associated articles from our dataset. Note that the text we include for each image is truncated, as many of the articles are quite lengthy. We also annotate each image with a "L" or "R" depending on whether the image comes from the left or right respectively, as well as the original source for the image and article text.

We believe these images highlight how extreme some of our media sources are. For example, in Fig. 7, we see an image of apparent Hispanic gang members with Obama's head cropped as one of them. The article discusses illegal immigration and alleges Obama has facilitated allowing "illegals" to stay. In Fig. 8, we see several images of protests, one of which is associated with the left and one of which is associated with the right. We note, however, that the protest image associated with the right (bottom left) actually shows protesters carrying signed *supportive* of Planned Parenthood, a topic associated with the left. A similar situation is found in Fig. 9 where we see an image of a transgender man (bottom row, middle) labeled right. These images' labels only makes sense in conjunction with their paired article text, which are describing circumstances related to the image. These examples underscore one primary challenge of learning visual classifiers on our dataset: *images' labels often depend upon the context on which they appear as much as they depend on what is in the image itself.* Thus, learning to predict the politics from an image is highly challenging due to the inherent high-level semantic nature of the problem as well as the presence of noisy data. We believe our method, guided by privileged information from the text domain helps guide the training and alleviates some of these problems.



Figure 4: Examples of images whose politics were correctly guessed by at least a majority (2/3) of MTurkers. We also include the reasons given for their prediction by the MTurkers below each image. MTurkers who guessed the image incorrectly are indicated by "Guessed incorrectly."

#### References

[1] Q. Le and T. Mikolov. Distributed representations of sentences and documents. In *Proceedings of the International Conference on Machine Learning (ICML)*, pages 1188–1196, 2014.

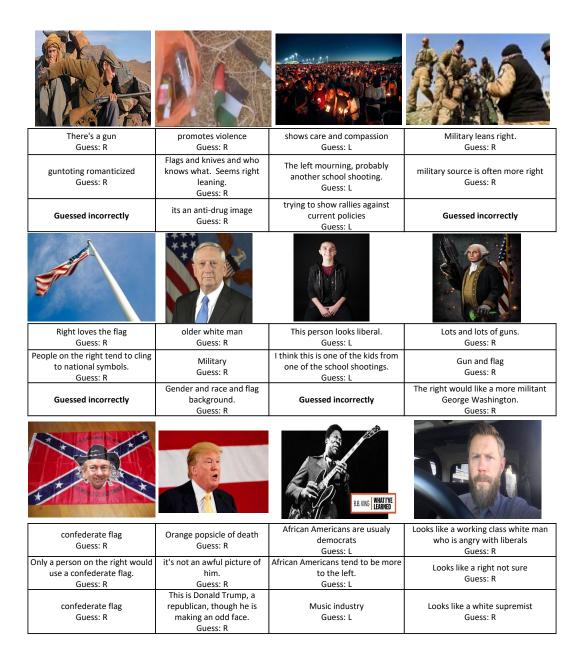


Figure 5: Examples of images whose politics were correctly guessed by at least a majority (2/3) of MTurkers. We also include the reasons given for their prediction by the MTurkers below each image. MTurkers who guessed the image incorrectly are indicated by "Guessed incorrectly."



Figure 6: Examples of images whose politics were correctly guessed by at least a majority (2/3) of MTurkers. We also include the reasons given for their prediction by the MTurkers below each image. MTurkers who guessed the image incorrectly are indicated by "Guessed incorrectly."



"She went in thinking that the usual liberal menu of anti-gun policies would reduce that number dramatically. She came out concluding that "the only selling point [of those policies] is that gun owners hate them." That's an interesting way to phrase leftist conventional wisdom in an era when the right's tribalism draws so much

R scrutiny."....
Source: HotAir.com



'The lamestream media told you: Illegals at the border have dropped to the lowest point in years, reports The Arizona Republic. The local newspaper reported that 3,100 illegal aliens had come across into Arizona, in a story, late last year. They didn't call them future democrat voters, as some critics claim. Actually, Border Patrol reports 479,371 apprehensions at the border for 2014, nearly a half million, or 39.947 per month on average, most of them in Texas. According to local experts, half a million people is a lot of mouths to feed. It's unclear what happened to them all, or if they'll become future democrat voters as critics claim. Obama has jumped through many hoops to allow many illegals stay in the country, using a pen and a phone, in apparent violation of law, Source: Ammoland.com



"The lower house of the Czech parliament has agreed to alter the constitution so that firearms can be held legally when national security is threatened. The amendment gives Czechs the right to use firearms during terrorist attacks. It was passed by the lower house by a big majority, and is likewise expected to be approved by the upper house."

Source: WND.com



"After a week full of tragedy, death and emotional exhaustion from the American public, a Black Lives Matter rally was quickly planned and hosted in downtown Des Moines this evening. Several young women took the lead in organizing the rally and march, mostly on social media and through personal networks. The result was impressive: around 400 people gathered at Cowles Common at 3rd and Walnut. Only a few blocks from my office, I decided to grab my camera and recorder to walk over after work. I came away from it an hour and a half later confused as to what it had accomplished. "
Source: lowaStartingLine.com



"Former White House chief strategist Steve Bannon told Axios that it's "impossible" that President Donald Trump would pivot to gun control now, warning that such a move would "be the end of everything." Despite taking a gun control stance in the past, Trump knows he got elected on an unambiguous pro-gun stance, and he enjoyed staunch support from the all-powerful NRA. Not even the worst mass killing in U.S. history would be enough to move the president off of that, Trump confidants told Axios. Source: NewsMax.com



"In 1999, two years before America's longest war would begin in Afghanistan, Lewis Sorley published a seminal work titled A Better War about America's last longest war that raged in the 1960s and 70s. The subtitle of this great work serves as the thesis of the book and says it all: The Unexamined Victories and Final Tragedy of America's Last Years in Vietnam . Effectively beginning when the 88th Congress enacted the Gulf of Tonkin Resolution in August, 1964, which authorized Lyndon Johnson to use military force in ... Source: RedState.com

Figure 7: Example images and articles (truncated) from our dataset. We annotate each image with the media source from which it and the article came, as well as the politics of that media source, as determined by Media Bias Fact Check (see our main text for details).



"When Jedi Jimenez approached the podium at the People's State of the City Thursday, he faced hundreds of Long Beach residents, crammed shoulder to shoulder in the pews of the First Congregational Church located downtown. Attendees shared one unifying goal: to take their city's issues head on. When Jimenez finally spoke, he didn't just ask for the crowd's attention -- he commanded it. "Over the past year, our country has faced some of the biggest threats to our values of democracy, inclusion and justice."

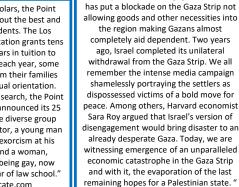
Source: Daily49er.com



"On January 23, 2017, the Senate confirmed Rep. Mike Pompeo, a Republican congressman from Kansas, as director of the Central Intelligence Agency. Pompeo, 53, has served in the House of Representatives since 2011. He succeeds a 25-year veteran of the CIA, John Brennan, who's served as the agency's chief since 2013. Advertisement -Continue Reading Below Here's what you need to know about Pompeo: 1. He served in the Army. Mike Pompeo during a TV appearance while he was a member of the Army. Pompeo graduated first in his class from West Point in 1986, according to his congressional biography." Source: Cosmopolitan.com



"Like a scout for scholars, the Point oundation searches out the best and brightest LGBT students. The Los Angeles-based organization grants tens of thousands of dollars in tuition to dozens of collegians each year, some cut off financially from their families because of their sexual orientation. Following a six-month search, the Point Foundation recently announced its 25 scholars of 2010. The diverse group includes a former janitor, a young man who underwent an exorcism at his mother's hands, and a woman. previously fired for being gay, now entering her third year of law school." Source: Advocate.com





"On Sunday, Senator Susan Collins (R-ME) said she would not vote for President Trump's nominee to the Supreme Court if the nominee was "hostile" to Roe v. Wade . This shouldn't come as a surprise; Collins showed how callous she was to the rights of the unborn child in 2003. On October 21, 2003, voting with ..." Source: DailyWire.com



Source: Electronicintifada.net

"Two years after disengagement Israel

"A Presbyterian chaplain in Maine penned an op-ed this month in a local newspaper in which he described Planned Parenthood as "blessed" and lauded the nation's largest abortion provider for promoting "life-affirming values." The Rev. Marvin Ellison, who ministers to patients at a Planned Parenthood facility in Portland, recently joined with other chaplains to host ..."

Figure 8: Example images and articles (truncated) from our dataset. We annotate each image with the media source from which it and the article came, as well as the politics of that media source, as determined by Media Bias Fact Check (see our main text for details).



"Steve Schlariet and Ozzie Russ say they never sought the spotlight of social activism, the spotlight found them. The rural Florida Panhandle couple could become one of the first gay men granted a license to marry in the state when a judge's order takes effect Tuesday. Together nearly 20 years and united during a commitment ceremony in Fort Lauderdale in 2001, the men live a quiet life raising horses and dogs on their central Panhandle ranch. When friends approached them about joining a lawsuit challenging the state's gay marriage ban, Schlariet, 66, and Russ, 48, were a bit reluctant."

Source: LGBTQnation.com



"The Obama administration is currently in the process of considering a series of measures to curb gun violence that would go beyond a ban on assault weapons and high-capacity ammunition, according to the Washington Post . Citing "multiple people involved" in the discussions, the Post says that a working group led by Vice President Joe Biden is considering several sure-to-be controversial measures, such as universal background checks, a system to track weapon sales and ..."



"Although the news media and Democrats believe government control of guns owned by Americans is politically necessary, what may be equally important is the investigation into the President Barack Obama-Secretary of State Hillary Clinton illegal weapons deal in Libya that helped to arm the Syrian-based Islamic State of Iraq and Syria (ISIS). The thinking in 2012 was that the fall of the Syrian dictator Bashar al-Assad made a U.S.-Muslim terrorist alliance worth the few negative news stories or Republican..."



"We are in the midst of Holy Week, a time filled with both highs and lows as we follow Jesus's path from crucifixion to resurrection. In the Christian faith, this is our most sacred occasion. It also serves as an opportunity to spend time with family and loved ones. Sadly, for too many people around the world, Holy Week is a dangerous time. This is especially true for Christians in the Middle East who suffer extreme persecution. In fact, groups like the Islamic State of Iraq and Syria (ISIS) search for and kill Christians simply because of their religious beliefs."

Source: YellowHammerNews.com

R

"A Catholic theology professor at the College of the Holy Cross in Worcester, Massachusetts is stirring up controversy on campus after a student journalist exposed some of his past writings arguing that Jesus was a "crossdressing," gender-fluid "drag king" who supported gay pedophilia. Senior student Elinor Reilly first wrote about Dr. Tat-siong Benny Liew, who serves as the college's Chair of New Testament Studies, in the college's independent student journal The Fenwick Review. As she explains. Liew has some .... Source: TownHall com



"The understandably angry and frustrated student survivors of the deadly school shooting that took place in Parkland,.. Fred Guttenberg, father to one of the teens slain in the massacre, confronted Rubio calling his comments in the wake of the shooting "pathetically weak." He called for the senator and the rest of Washington to do something about the gun problem plaguing America, but Rubio's response was about what you would expect, refusal to acknowledge the need for stricter gun laws saying, "the problems we are facing here today cannot be solved by gun laws alone. Source: TheMayen net

Figure 9: Example images and articles (truncated) from our dataset. We annotate each image with the media source from which it and the article came, as well as the politics of that media source, as determined by Media Bias Fact Check (see our main text for details).