Automated Visual Clustering: A Technique for Image Corpus Exploration and Annotation Cost Reduction*

Andreu Casas[†] Nora Webb Williams[‡] Kevin Aslett[§] John Wilkerson[¶]

Preliminary draft: please do not circulate without permission of the authors.

Abstract

Compared to text and voice, images can be an especially effective form of political communication. It is now relatively easy to automatically label images for many categories of interest (such as protests, famous people or facial expressions). As a result, scholars are increasingly using large-N image analysis to investigate contemporary political attitudes and behavior. We address two emerging needs of image scholarship. The first is that researchers may want to visually explore an image corpus to discern patterns before they begin assigning labels. This can be difficult with very large corpora. The second is that researchers may be interested in image categories that cannot be easily assigned using off the shelf automated methods. We demonstrate how unsupervised image clustering can help researchers to address both of these needs more efficiently. Our substantive focus is on exploring and labeling a large corpus of images shared by Twitter users along with the hashtag #FamiliesBelongTogether.

*Research supported by NSF Grant Number 1727459, "The Power of Images: A Computational Investigation of Political Mobilization via Social Media."

[†]Reserach Fellow, *University of Amsterdam*: a.casassalleras@uva.nl

[‡]Assistant Professor, *University of Georgia*: norawebbwilliams@uga.edu

[§]PhD Candidate, *University of Washington*: kevina4@uw.edu

[¶]Professor and Chair of Political Science, *University of Washington*: jwilker@uw.edu

1 Introduction

Visual information has become an increasingly important form of communication due to the rise of digital media and mobile communications (Casas and Webb Williams, 2018). Visuals are also an especially effective form of communication when compared to text and voice. People are more likely to notice visuals, recall them, and be moved by them (Nelson et al., 1976; Grabe and Bucy, 2009). They deserve more attention from scholars studying subjects where visuals are of particular relevance, such as agenda setting, issue framing, public opinion formation and social movements.

Until recently, the high costs of labeling images for content discouraged all but the smallest projects. Computer vision methods now make it much easier to assign labels to thousands or even millions of images. Any social scientist with an image dataset can take advantage of state of the art computer vision algorithms (convolutional neural nets or CNNs) through on-line commercial image labeling services offered by Amazon, Google, Microsoft and others. Scholars with modest programming skills have a number of open-source (free) pre-trained algorithms that they can easily access through deep learning libraries such as TensorFlow, Keras, or PyTorch. Scholars can use these existing algorithms to predict the labels they have been trained to predict (for example, the 1,000 categories/objects in the ImageNet corpus), or they can also fine-tune a the algorithm to assign new labels (typically with a much smaller number of training examples) (Webb Williams et al., 2019).

But there are still situations where off the shelf computer vision methods do not fully serve the needs of social science researchers. We highlight two of these and show how unsupervised image clustering methods can help to address them. The first is when a researcher does not know, *ex ante*, what categories of an existing image classification system are relevant for a project. For example, they may be interested in the symbols of collective identity being used in protests. For a small project they can simply look at images from those protests.

However for a large project that includes thousands or millions of images, discovering the relevant categories can be much more challenging.

The second situation is when a researcher wants to collect image information not obtainable using existing computer vision tools. For example, existing algorithms are very good at labeling for objective features, such as vehicles, celebrities, or facial expressions. Scholars are presumably also interested in subjective reactions to images, and the impact of those reactions on behavior and attitudes. There has been much less work on such evoked emotions. Fine tuning existing image classification models does not appear to perform well at predicting the emotions that large datasets of images evoke to people (Webb Williams et al., 2019). The only practical alternative may be manual annotation, but it can be prohibitively expensive and time consuming, specially given that different groups of people may have different subjective reactions and so the same image may need to be labeled multiple times.

We show that unsupervised image clustering provides a way to more easily explore a large corpus of images. In this respect it serves a purpose similar to unsupervised topic modeling, which was originally developed to enable researchers to explore and discover common themes within large text corpora. Unsupervised image clustering can also substantially reduce manual image annotation costs in situations where automated image labeling is not an option. Once again, there is a parallel in topic modeling research where discovered topics often serve as the starting point for developing more rigorous classification systems.

For a textual analysis, co-occurring words are the features used to cluster documents into topics. Images, in contrast, are comprised of three dimensional (red, blue, green) collections of pixels. How can this pixel information be used to meaningfully cluster images? One option might be to use off the shelf tools to classify images before clustering them. But that puts the cart before the horse because a project goal may to be discover new image clusters that transcend existing classification systems.

Our approach uses the embeddings of a supervised deep learning convolutional neural net.

In supervised image analysis, embeddings are reduced multidimensional pixel information that are used to assign images to classes. We use the same penultimate information to cluster images (without forcing them into a limited number of pre-determined classes).

A researcher can then draw random examples of images from each of the clusters to explore a large corpus. The intuition for using unsupervised image clustering to assist manual annotation is similarly straightforward. Clusters represent thematically similar images. Instead of having to label these images individually, the annotator labels a small sample. Those labels are then propogated to all of the images in the cluster. We demonstrate that this labeling short cut can produce accurate results at much lower cost.

To demonstrate the method we investigate emotional responses to images posted on Twitter in response to the Trump Administration's policy of separating migrant children from their adult family guardians at the US-Mexican border. We first show how unsupervised image clustering facilitates the exploration of a large and rich image dataset (xx total images including xx unique images). We then illustrate how it can be used to efficiently label #FamiliesBelongTogether images for the emotions they evoke in viewers of different political persuasions (Republicans *v.* Democrats).

2 The power of images

Compared to text and voice, visuals are a superior form of communication (Nelson et al., 1976). Images are more likely to capture people's attention. Eye-tracking studies find that people pay particular attention to visuals when reading the news (Dahmen, 2012). People are also more likely to recall visual information. Paivio et al. (1968) showed that subjects were more likely to remember the ordering of a list of objects from pictures than from names. Visuals also generate stronger emotional reactions than text (Grabe and Bucy, 2009).

Studies suggest that images are also important for understanding political attitudes and

behavior. Numerous articles find that voters judge candidates differently based on their looks, that respondents who watch more television are more likely to use looks as a voting cue, and that conservative parties in Europe benefit from the fact that their candidates are generally judged to be better looking (Todorov et al., 2005; Poutvaara, 2017). In a widely covered *Science* article, Todorov et al. (2005) also demonstrated that looks impact electoral success. They asked subjects to choose the most competent U.S. congressional candidate after looking at their pictures for just one second. They report that respondents' choices correctly predicted 70% of the race outcomes (in which they knew nothing else about the candidates), and correlated with margins of victory. Beyond candidate looks, however, research on the political power of images is limited. In a recent study of a Black Lives Matter protest event, Casas and Webb Williams (2018) found that images evoking enthusiasm or anxiety were positively related to greater attention to and sharing of Facebook and Twitter messages. There is believe that this sharing had tangible effects because other studies of the same movement found that social media penetration was predictive of on-street support and mobilization (De Choudhury et al., 2016; Freelon et al., 2016).

Many of the studies cited above involved experiments with a small number of images. The latter Black Lives Matter study was based on a relatively modest sample of few thousand social media images. The increasing importance of social media as an information source and means of communication makes it increasingly important to be able to systematically study much larger corpora. The recent availability of computer vision methods have opened exciting opportunities. Any researcher can now use existing off the shelf tools to label inamges for a large number of pre-existing content categories. Open source tools can also be fine tuned to assign new labels. Won et al. (2017), for example, uses a fine-tuned Convolutional Neural Net to detect the presence of violence in protest-related images with the goal of studying its impact on future protest participation. These opportunities also extend beyond simply tagging images for content. In a study of voting fraud in Mexico, Cantú (2019) train a CNN

to detect alterations of vote tallies.

However, trained CNNs may be of limited value when the pre-defined classes do not map with the objectives of a specific project. For example, symbols of collective social identity (Tajfel, 1981) can activate feelings of group belongingness that increase voter turnout (Gerber et al., 2008), influence attitudes on particular issues (Hassin et al., 2007), and inspire protest participation (Kharroub and Bas, 2015; Casas and Webb Williams, 2018). Some symbols of collective identity (such as a flag) can be detected using existing CNNs. But relying on existing CNNs also limits the potential scope of such a study in important ways. Symbols of collective identity are often intentionally obscure and ephemeral. Existing CNNs will not detect Pepe the Frog or gestures such as the 'OK' hand sign, two important symbols of far right groups. It is also well known that censorship forces chinese dissidents to use pseudonyms and, one suspects, visual pseudonyms.

Transfer learning, where a pre-existing CNN can be fine tuned using a relatively small sample of images of a new class, can address the challenge of labeling images for newly discovered symbols of collective identity. But how does a researcher discover them in the first place in a corpus of thousands of millions of images?

Commercial and open source CNNs may also not predict theoretical mechanisms of interest to social scientists. They are amazingly good at object detection. They can identify thousands of common objects of interest and, through transfer learning, can be adapted to new objects of interest (Webb Williams et al., 2019). Much less work has focused on subjective image labeling. Yet, where symbols of collective identify are concerned, the object is less important than the emotion it evokes. Moreover, the same object may evoke different emotional responses in different viewers.

Emotions are an important phenomenon in politics. Research finds that emotions influence attitudes on issues and behavior in a range of participatory settings (such as elections and social movements) (Valentino et al., 2011; Marcus et al., 2000; Clifford and Piston,

2016). Existing affective models point to a range of emotions as strong political motivators, including enthusiasm, anxiety, and anger (Marcus et al., 2000, 2017).

Some computer vision models predict whether people in images *look* angry, sad, or happy (Busso et al., 2004), while other research predicts whether an image evokes generally positive or negative feelings in the viewer (Xu et al., 2014). This work is importantly incomplete in that social science research finds that some negative emotions (e.g. anxiety) encourage mobilization and support, whereas other negative emotions (e.g. sadness) have the opposite effect (Marcus et al., 2000). In addition, whether I feel sad after observing a sad face (e.g.) probably depends on the context. For example, I may feel very differently if the person in the image is a member of a political outgroup.

The limited computer vision research that does attempt to predict a broader range of evoked emotions has not produced accurate results. Peng et al. (2015) trained a CNN to predict images evoking anger, fear, disgust, and sadness, achieving average accuracy of just 65% (based on a balanced dataset). Webb Williams et al. (2019) also experienced limited success when using transfer learning to predict evoked emotions.

The poor performance of automatic classifiers designed to predict evoked emotions means that researchers interested in studying how emotional responses impact attitudes and behavior must rely on manual image annotation. For larger projects (such as those examining social media), manual annotation can be prohibitively expensive.

Unsupervised visual clustering can help to address both these issues. It can facilitate the exploration of large image corpora with the goal of identifying image classes relevant to a project's goals. It can also substantially reduce manual annotation costs in situations where existing computer vision tools are impractical.

3 A New Automated Visual Clustering Method

We propose a visual clustering method that can be used to discover new meaningful patterns within large volumes of images, and to reduce annotation costs by apply the same labels to clusters of similar images. In contrast to prior research, this method does not presume a preexisting set of possible cluster categories. There are three main challenges to building such a method. First, we need to represent images numerically in order to then be able to apply a clustering algorithm to the image corpus. Second, as with all clustering methods, the method requires that we designate a criterion for selecting the appropriate number of image clusters. Finally, we need to a method for evaluating and selecting the best performing algorithm. In this section we discuss how we address each of these challenges.

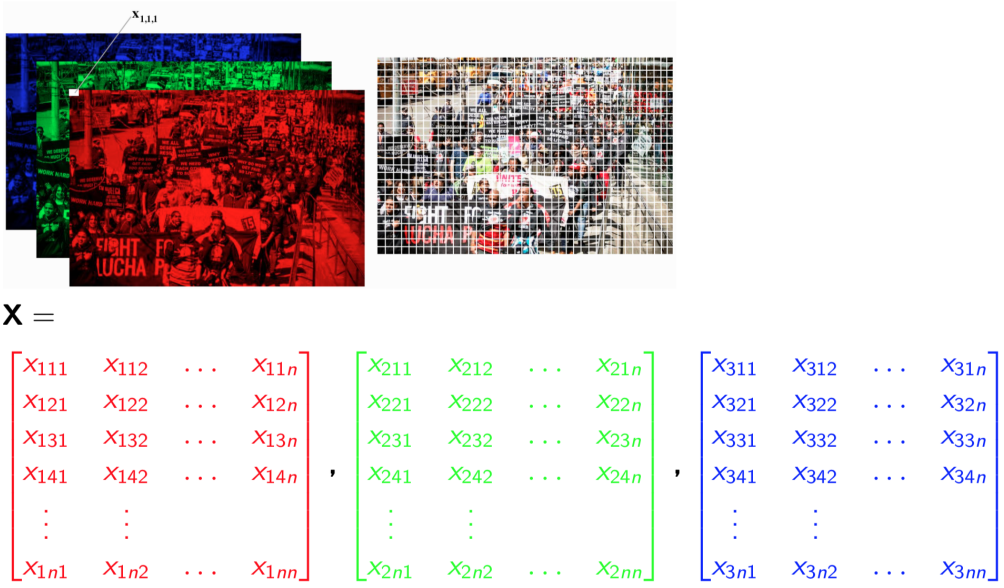
3.1 Example Image Dataset

Throughout the paper we will use the same example image dataset of our own to clearly illustrate how the proposed method works. In the autumn of 2017, we began a substantial Twitter collection effort for studying social movement support. We simultaneously gathered tweets by entities who are often the originators of social movements, including a large number of USA-based public affairs organizations and politicians, as well as all tweets (by anyone) that included hashtags used by these entities. The hope was that we would capture social movement successes and failures rather than just the successes. From this universe of hashtags (and tens of millions of tweets) we selected the #FamiliesBelongTogether for the current paper. This corpus contains 174,172 tweets (and 88,075 images; 18,096 unique) collected between May 30th and October 27th, 2018. Appendix A provides further details about the data collection process.

3.2 From Images to Data

Images are typically represented as three-dimensional matrices, where each matrix represents the intensity of red, green, and blue in a particular pixel of the image (standardized values ranging from 0 to 255, see Figure 1). Though numeric, these raw representations are not very useful for clustering images because they are very large matrices that make comparisons resource intensive and because they are not very discriminating from a thematic perspective.

Figure 1: An image represented as a 3-dimension input. Each $X_{i,j,z}$ unit contains information about the pixel-level intensity of red, green, and blue in the image.



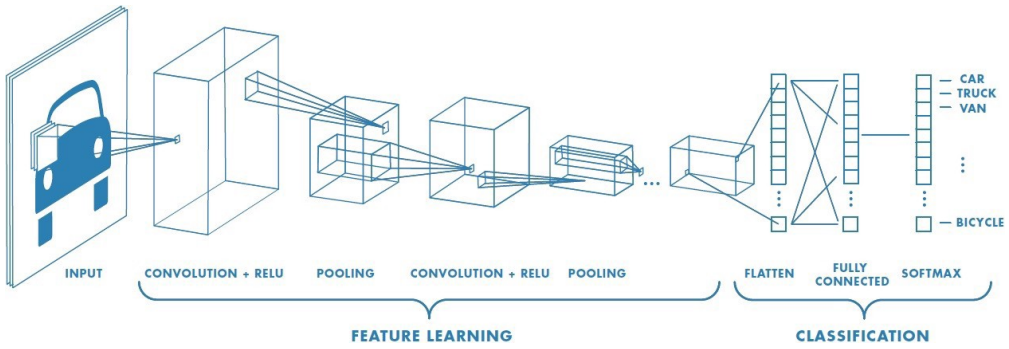
CNNs start with these three dimensional matrices as inputs and ultimately transform them to flatter representations. The architecture of each model varies, but the output embeddings represent images in a denser and lower dimensional space (e.g. 512-size vectors). The final step of a supervised method is to compute the probability that the image is in fact a chair (or a horse, etc.) based upon the similarity of this embedding to the embeddings of other labeled examples (see Figure 2 for an example of a CNN architecture).

For an unsupervised approach, embeddings are much easier to work with than the original three dimensional representations. They are also an effective way to capture not only the

visual but also the thematic similarity of images before forcing them into specific classes. A model trained to predict the 1,000 ImageNet classes for example has already learned that two chairs that look very different are indeed two instances of the same class, which means that the image embeddings generated by the model already carry some sort of human "meaning".

An approach to generating image embeddings for a corpus of interest would be to pass all images through a model pre-trained to predict these ImageNet categories. However, the "meaning" carried in these embeddings may fail to capture additional meaning of interest to the researcher. It could therefore be that, for example, images evoking similar emotions are not close to one another in this embedding space.

Figure 2: A Convolutional Neurat Network (CNN) for image classification



Note: Credit: Sumit Saha at https://towardsdatascience.com

A better approach then may be to fine tune an open-source pre-trained model before using it to generate image embeddings, this way one takes advantage of a model that has already learned from hundreds of thousands of examples while also making sure that the model captures (at least partially) the additional 'meaning' of interest to the researcher.

In order to be able to evaluate both approaches, we labeled a small set of images drawn from tweets using the #FamiliesBelongTogether hastag (N = 609). Six annotators annotated (using binary judgements) each of the 609 images for elements that are theoretically relevant to us (the evoked emotions we focus on this paper plus some additional features in which we are interested in a related project): a) the emotions the image evoked (enthusiasm, anger,

and anxiety), b) whether people of different ethnicities were present in the image (white, black, Asian, and Latino), c) the gender of those people (male and female), d) whether a child was present, e) whether a symbol of collective identity was present, and f) whether annotators thought that the image communicated that the movement could be successful at accomplishing their goal.

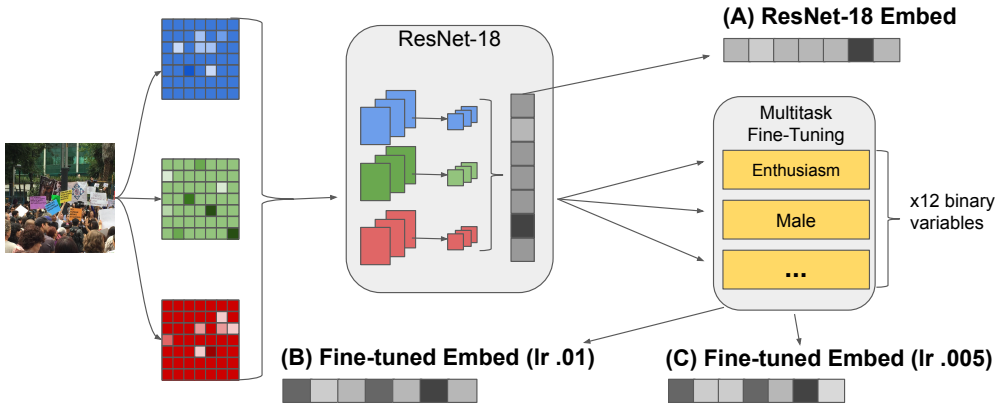
We then fine-tuned a pretrained (ResNet-18) computer vision model (He et al., 2015) with this information by replacing the last fully connected layer with a new one predicting 12 rather than 1,000 classes, and then retraining the model weights for 50 additional iterations using our annotated dataset. Instead of using a softmax function predicting the probability of each image belonging to one of a set of mutually exclusive classes (probabilities adding up to 1), we used 12 sigmoid functions independently to predict the probability of each of the 12 labeled non-mutually exclusive items to be in the image (a process known as multi-task learning, (Caruana, 1997)). We repeated the process twice, the first time using a learning rate of .005 and the second time using a learning rate of .01.

Once these two new ResNet-18 models were fine-tuned, we passed the rest of the images in our dataset through them and pulled the output of the second-to-last fully connected layer. As shown in Figure 3, in the end, we ended up with three types of image embeddings representing the images in our dataset in a denser and lower dimensional space: A) the embeddings directly generated with the pretrained ResNet-18 model (*ResNet-18 Embed*), B) the ones generated after the multitask fine-tuning of ResNet-18 using a .01 learning rate (*Fine-tuned Embed (lr .01)*), and C) the ones generated after fine-tuning ResNet-18 using a .005 learning rate (*Fine-tuned Embed (lr .005)*).

3.3 An Iterative Clustering Method

After transforming the images to lower dimensional embeddings representing both the look and meaning of the pictures, we proceeded to grouping similar images in an unsupervised

Figure 3: Three types of embeddings used for image clustering.



fashion using a k-means algorithm, a common clustering method in machine learning research (Jain, 2010). One option was to fit a single k-means model to the matrix of image embeddings. However, as we will show in the next subsection, this approach did not produce very satisfactory results. Instead, we decided to employ the iterative approach sketched in Figure 4 and that we describe below.

We run the following 5 steps for several iterations. (1) First we decide the number of clusters to be "discovered" by the k-means algorithm in that iteration. In order to do so, we fit several k-means models, increasing the number of clusters by N each time (*Step Size*, e.g. +5 clusters), and measuring the model fit. To speed up the process, we use a random subsample of the images to perform this task (*Sample Size*, e.g. 1,000 images). We consider that we have found the number of clusters that best describes our data once the average of the goodness of fit for the last I runs does not improve (*Converge Window*, e.g. 3 iterations).[1]

Then, the second step (2) in the process is to fit a k-means algorithm with that particular number of clusters to the whole image dataset. (3) Next, we evaluate the cohesiveness of the clusters using the average of the silhouette score for the images in each cluster.[2] (4)

[1]We average the goodness of fit measures across the last I runs to make sure that the decision is not based on an isolated run of the model and so to make sure that the fit of the model does not improve as the number of clusters increase.

[2]A silhouette score measures both how similar images classified in the same cluster are to each other as well as how far apart images classified in different clusters are to each other. It measures both the

Clusters of images that have a silhouette score of over a threshold (*Similarity Threshold*, e.g. 0.4)[3] are identified. (5) All the images within clusters that receive a silhouette score above the *Similarity Threshold* are pulled out of the corpus of images. After these images are pulled out and these clusters of images are saved, we run all five steps again on the remaining images, and we keep repeating the process until we run out of images to cluster or the number of remaining images is to low (e.g. 20 images left, *Stop Size*). In the next section we demonstrate that this iterative approach performs better than a single-shot k-mean clustering. Moreover, notice that in the description of the method we have mentioned five hyperparameters for which the researcher needs to choose values (sample size, step size, convergence window, similarity threshold, and stop size – these (and sample values for them) are also underlined in Figure 4). In the next section we also explain how to judge which hyperparameter configuration works best.

Figure 4: Pseudo Code of the Iterative Clustering Method

X = input image matrix (e.g. 20,000 images × 512-size embeddings)
1. Find number of K clusters to fit
   (a) Randomly sample 1,000 [*Sample Size*] images from X
   (b) Iterate through new values of K (increase K by 5 [*Step Size*] each time)
      - fit k-means algorithm (for K clusters)
      - check average goodness of fit for the last e.g. 3 iterations [*Convergence Window*]
      - stop if goodnes of fit does not improve OR if $K >$ images in X. Continue otherwise.
2. Fit k-means algorithm to X predicting K image clusters
3. Calculate intra-cluster similarity (silhouette score)
4. Find cohesive clusters (cluster silhouette score > e.g. 0.04 [*Similarity Threshold*]
5. Separate out from X the images from clusters found to be cohesive in step 4.
   - If still more than e.g. 20 images in X [*Stop Size*]: STOP. Otherwise, run another iteration.

cohesiveness of a cluster and its distance from other clusters.

[3]Silhouette scores range from -1 and 1, 1 being the highest level of cohesiveness and uniqueness, and -1 being the lowest level of cohesiveness and uniqueness.

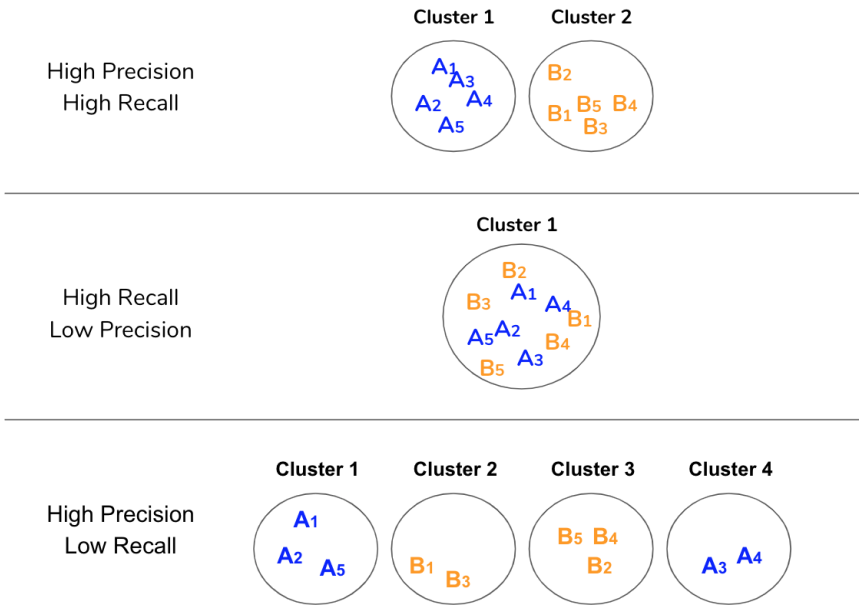
3.4 Validation

We created a gold standard dataset in order to know which lower dimensional image representation, and hyperparameter configuration, do a better job at clustering together images that are similar on the dimensions that we care (e.g. evoked emotions). We manually annotated a set of image pairs from our #FamiliesBelongTogether for whether we believe they should be classified into the same cluster. We used two main criteria when making this call: a) the images in the pair had to be instances of the same element (e.g. a protest, a sign, the same person, etc.), and b) the images had to be likely to evoke the same or very similar emotional reactions if coded by the same person. The former is crucial to make sure that the resulting clusters do a good job at representing the different types of images in the corpus, and so to ensure that the clustering technique serves the "corpus exploration intention" well. The latter is key to make sure that the resulting clusters are as cohesive as possible on the theoretical mechanisms of interest (evoked emotinos), and so to ensure that we can then perform label propagation within the clusters and use them to "reduce image annotation costs."

A simple exploration of the unique images in the #FamiliesBelongTogether corpus revealed a very unbalanced dataset, with a large number of images clearly being instances of the same elements (e.g. images of letters directed to public representatives, instances of street protests, etc.). A random sample would yield very similar image pairs, missing example pairs from numerous potenial future clusters. To account for this lack of balance, we first fit a 80-cluster k-means algorithm on the #FamiliesBelongTogether images.[4] and from each resulting cluster we randomly sampled pairs of images (554 pairs in total). The annotators judged cohesiveness among these image pairs very similarly (87% agreement between two annotators and a Cohen's kappa value of 0.64).

[4]We decided this number of clusters after a goodness of fit analysis in which we evaluated fitting a varied number of clusters.

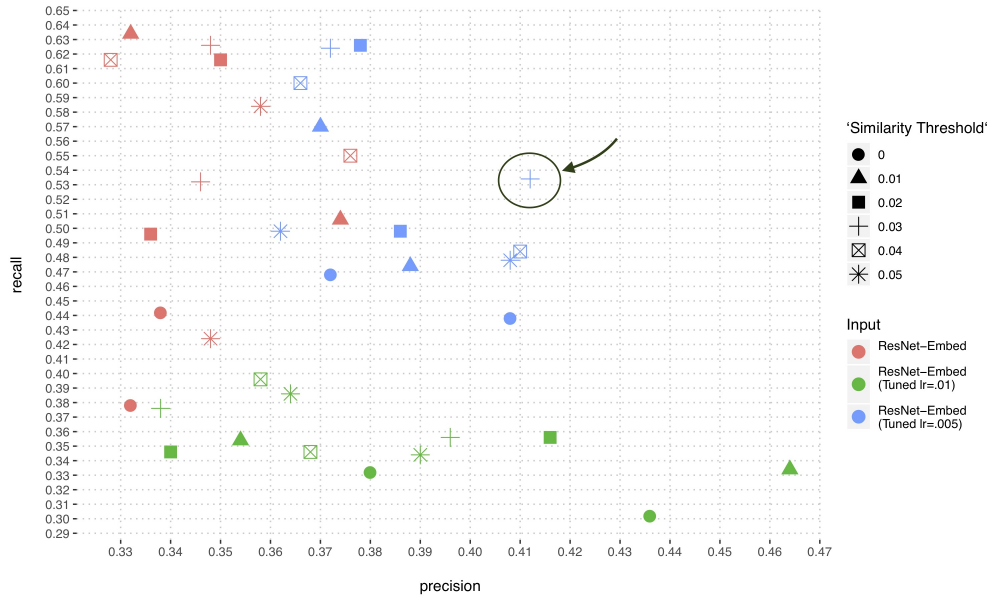
Figure 5: Precision and recall for 3 possible ways of clustering 5 images known to be of category A and 5 images known to belong to category B.



We then use the gold standard dataset to perform a grid search and assess the precision (proportion of pairs correctly predicted to belong to the same cluster) and recall (proportion of pairs labeled as belonging to the same cluster that have been classified as such) of the three types of image embeddings and of different values for the five hyperparameters involved in the iterative clustering process. In particular, we tried all possible combinations of the following hyperparameter values, {3, 5} for step size, {0.0, 0.01, 0.02, 0.03, 0.04, 0.05} for the similarity threshold, and we kept constant a sample size of {1,000}, a stop size of {20}, and a convergence window of {3}.

We are interested in finding the type of input and hyperparameter configuration with the highest precision but also the highest recall. In Figure 5 we use a toy example to clearly illustrate why. High recall but low precision (second scenario from the top) means that we are correctly clustering images that should go together, but also images that should not. This is usually a sign of having fewer clusters than we should. High precision but low recall

Figure 6: Performance of Different Hyperparameter Configurations and Types of Image Embeddings



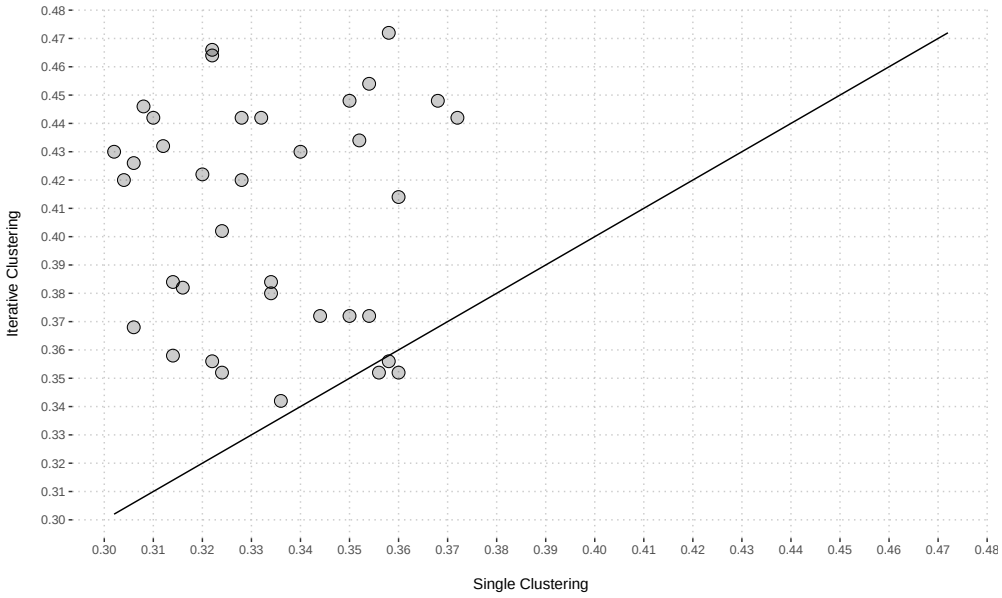
(bottom scenario) means that we are correctly not clustering images that should not go together, but it also means that we are splitting into different clusters images that should be grouped in the same cluster. Hence, when performing the grid search, we are interested in the performance that get us closer to the high precision and high recall scenario at the top of Figure 5.

Figure 6 shows the results of the grid search, based on a 5-fold cross validation. We observe that the best preforming clustering model (circled blue cross) uses the embeddings generated with ResNet-18 fine-tuned with a learning rate of 0.005, and a similarity threshold of 0.03 when discriminating non-cohesive groups of images during the iterative clustering process. In the subsequent sections of the paper we will use this model to illustrate how the resulting clusters can be used for corpus exploration and for reducting the image labeling costs.

Finally, in Figure 7 we take advantage of the creation of this gold standard dataset to also assess whether the iterative clustering option outperforms the one-shot k-means clusterings.

The F-scores (average precision-recall) is practically always higher for the iterative option.

Figure 7: Performance of Single *versus* Iterative K-Means Image Clustering

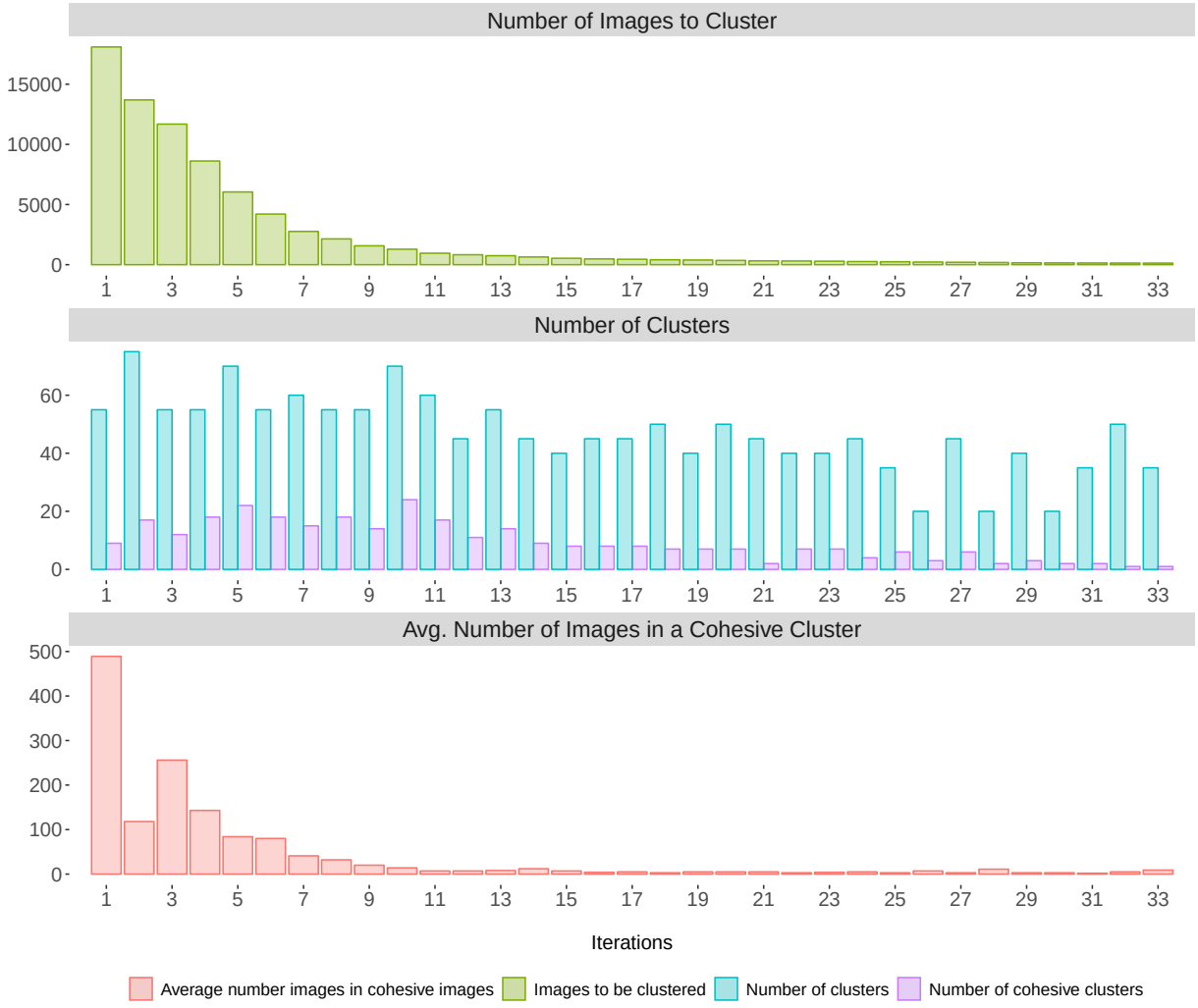


3.5 Best preforming model

In Figure 8 we provide further information about the best performing cluster. The algorithm run for 33 iterations and it generated 309 image clusters. In the top panel we observe that most images were classified into cohesive clusters in the first 10 iterations. In the middle panel we see that the number of clusters to be fit at each iteration remained quite constant, around 55 (light blue bars). The purple bars indicate how many of these clusters can be considered cohesive after discriminating based on the silhouette score and the similarity threshold. We observe fewer cohesive clusters to be found in the final iterations. Finally, in the bottom panel we report the average number of images grouped in the cohesive clusters found at each iteration. We see that in the first iteration the algorithm found some big groups of images: the cohesive clusters found in the first iteration had an average of about 500 images, aproximately. Then, we still see the algorithm to find relatively large clusters

unitl the sixth iteration. The cluster found in later iterations are much smaller, which as we see in the top panel, is also a function of not that many images being left to be clustered.

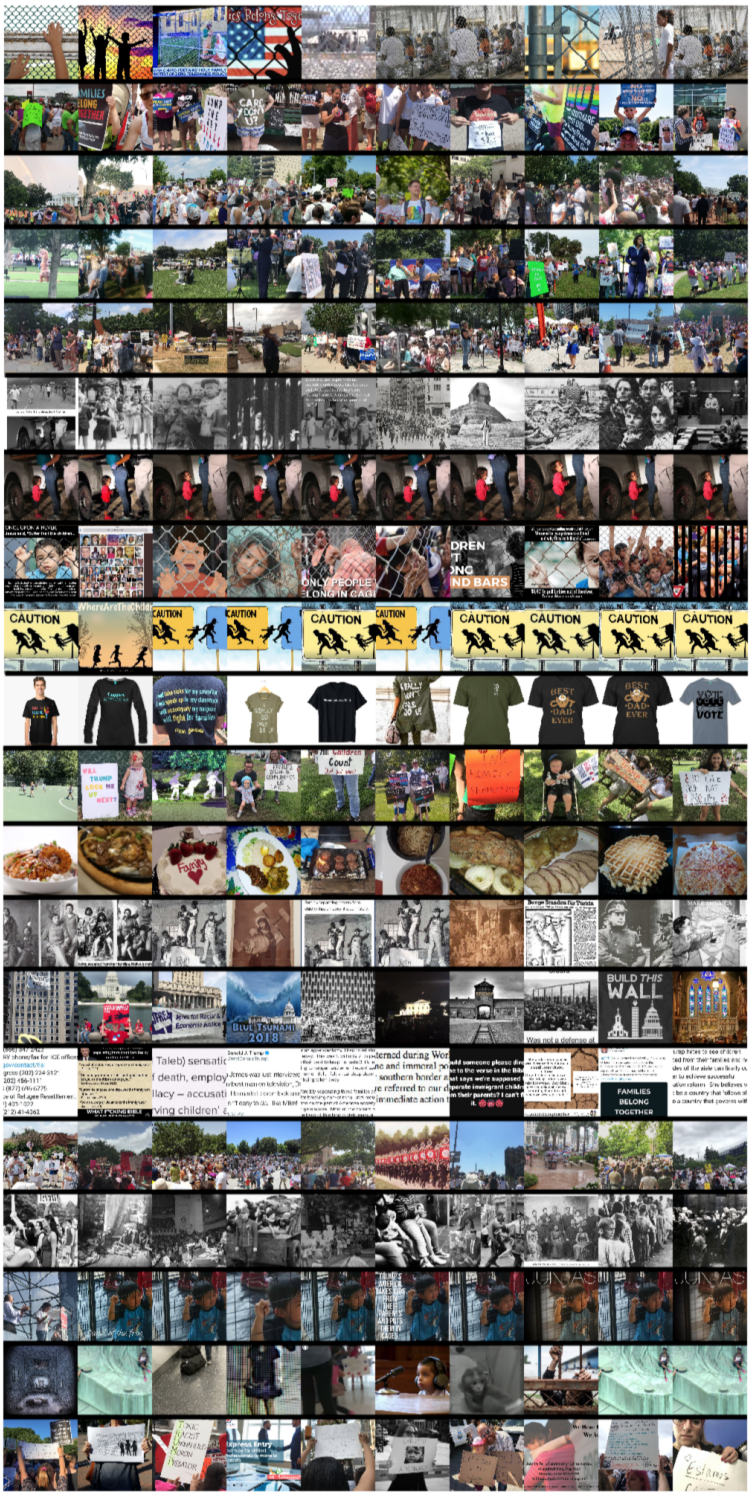
Figure 8: Information about the iterative progress of the best peforming model



4 Corpus exploration

Once images have been clustered, researchers can randomly sample some images from each group in order to explore the data at hand. In Figure 12 we show ten sample images from twenty of the 309 clusters genereated by the best performing model. Both the clusters and the images have been randomly selected.

Figure 9: Sample images from 20 random clusters



First, the figure illustrates how the method can help researchers get a sense of the type of data they are working with. For example, several clusters are clearly related to social and protest movement: rows such 2, 3, 4, and 5 show clusters of different types of images of street protests. However, there are also some types of images that a researcher studying the diffusion of this social movement on social media may have not expected, such as images with different kinds of food (row 12). The method helps the researcher to better identify, analyze, and understand particular part of the data as well as the dataset as a whole.

This exploration technique also allows the researcher to get a better sense of the different ways in which theoretical mechanisms of interests can be represented in the data. For example, for those interested in images as framing mechanism (Torres, 2019), the method allows them to see the range of ways in which people framed the movement. There are several mobilization clusters, with people protesting on the street (such as rows 2, 3, 4, and 5), but also several clusters of images with children behind fences (row 18) or in cages (row 8), children in general (row 11), and there are some clusters of images portraying immigration detention centers as nazi concentration camps or slave plantantions (row 13). The inital exploration can help those studying framing to elaborate a more detailed codebook that they can later use to conduct a more systematic analysis of the frames used (or not) when discussing the movement.

Finally, this clustering technique can also help explore the corpus of data by running some preliminary descriptive analysis in the same way people often use the output of unsupervised topic models (such as LDA) for text. Continuing with the framing example, a researcher interested in whether i.e. conservative people are more likely to engage with a particular type of frame than liberals, can code the 309 clusters for whether they have that particular frame, and in conjunction with Barbera (2015)'s method for estimating the ideology of Twitter users, analyze the proportion of conservative *v.* liberal users who engaged with (i.e. shared) images that contained that particular frame.

5 Reducing Annotation Costs

Leveraging the unsupervised clustering method, our next technique serves to reduce the substantial financial burden of manual annotation of images by producing accurate image annotations for a fraction of the cost of annotating all images within a dataset. By clustering a large corpus of images into groups of images that are cohesive and then labeling only a subset of images from each cluster, researchers can save on manual annotation costs. This will make image analysis more accessible across the discipline of social science. For example, if the unsupervised method identifies a cluster of 100 images that are objectively and subjectively similar, there is no need to have an annotator annotate each image from the cluster. Rather, we could take a sample of images from the cluster (5 images, for example) and only invest in annotating those images. With the scores from those 5 images we can build a distribution of labels and then draw from that distribution to label the other images within the cluster. This drastically reduces the cost of annotating images without compromising accuracy. Clearly, the effectiveness of this technique relies on clusters that are cohesive on the dimensions of interest to the researcher. In other words, on the assumption that the same respondent would code the same (or very similar) all imges in a cluster for a given feature (e.g. evoked fear) needs to hold.

5.1 An application

We use this method to annotate the images in the #FamiliesBelongTogether dataset for the emotions they evoke, with the particular objective of studying the extent to which emotional responses to images are in part to blame for the online diffusion of the movement. However, this is a very fleixble method that can be used to manually annotate any image dataset and for any research purpose.

First, we sample images from each of the 309 clusters. For those clusters with more than

5 images (N = 200 clusters), we sample 5 instances at random (N = 1,000 images). For those with 5 images or less (N = 109 clusters), we select all images but one for annotation (N = 223 images). In sum, we select 1,223 of the unique 18,096 images (about 5% of them) for manual labeling.

An important element to take into account is that some image features of interet to researchers are more subjective to annotate than others. For example, judging whether an image evokes anger is more subjective than coding it for whether it depicts violence. Hence, if the goal is to fully understand how a population responds to exposure to a set of images, researchers need to consider which coder characteristics can be predictive of the coding subjectivity. For example partisanship is likely to be predictive of how people feel when seeing images related to a political movement such as Families Belong Together, so the images selected for manual labeling should be annotated by Democrats and Republicans in order to understand the impact the images had on the population. Additional coder features to consider can be determined after coding a first small set of the sampled images and evaluating what personal characteristics predict coding variance. However, to keep things simple, in this illustrative example we only take partisanship into account and have each of the 1,223 images coded by a self-reported Democrat and a Republican.

After selecting the images, we recruit annotators on Qualtrics. We focus on labeling for 10 self-reported evoked emotions that are known to be representative of (and load onto) 3 emotional dimensions crucial for the study of politics: enthusiasm, aversion, and anxiety (Marcus et al., 2000, 2017). Annotators are asked to rate, in a 0-10 scale, how much they feel the following emotions when seeing images from the Families Belong Together dataset: hopeful, proud, and enthusiastic (*Enthusiasm* dimension), angry, hateful, bitter, and resentful (*Aversion* dimension), and afraid, scared, and worried (*Anxiety* dimension). For each sampled image, we obatin information about how much of the 10 emotions it evoked to a Democrat and a Republican.

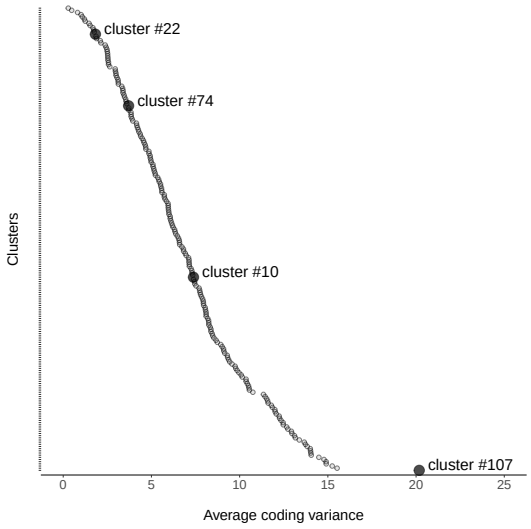
Despite being statistically cohesive, not all the 309 image clusters are choesive for the goal at hand. For example, in row 15 in Figure 12 we see images that are very similar from a visual perspective, but since they contain text, the actual statements may generate very different emotions to people, making the cluster actually non-chosive if the goal is to study the effect of emotional reactions to the images. Annotation cohesiveness is a crucial assumption of the proposed method.

We assess annotation cohesiveness for each cluster i and evoked emotion j by looking at the variance σ^2 of the score given by coders from party z to each image i selected from that cluster. Then we calculate the average variance across emotions and parties: $\sum_1^z \left(\sum_1^j (\sigma_{ijz}^2) \right)$. In Figure 10a we report this coding variance for each cluster (sorted from least to most variance). We observe the images from some clusters to have been scored very similarly for the emotions they evoked, and so the variance for some clusters to be low. The top two clusters in Figure 10b are good examples (coding variance of 1.82 and 3.71, respectively). The first one (cluster #22) contains similar images of protesting crowds and the second one (cluster #74) contains only images of children sleeping on the floor of detention camps. In the third row we observe four images from a cluster (#74) with higher coding variance (7.38). This cluster is similar to cluster #22 (images of protesting crows) with one important exception: there is an image of a nazi army. The algorithm classified these together because the latter is visually similar to the ones with people protesting on the street, it shows a group of people standing together. However, people of course reacted very differently to it, increasing the variance of the cluster. Finally, in the last row of Figure 10 we have four sample images from a melting pot cluster in which unrelated images were grouped together.

After coding a sample of images from each cluster, the next step for reducing image annotation costs and to move forward with studying any visual effect of interest (e.g. how emotions evoked by visuals contributed to online mobilization) is to propagate the labels provided by the annotators for a given cluster, to all the images in that cluster. However,

Figure 10: Cluster-level coding variance

(a) Distribution of the cluster-level coding variance.



(b) Examples of clusters with very low, low, high, and very high clustering variance

**Note:* This figure is currently based on data for 214 of the 309 clusters. We're still working on labeling the images for the other clusters.

a key assumption for the label propagation method to fulfill its purpose is that the same labeler (or type of labelere, e.g. a Democrat) will code any image from a given cluster very similarly. The high coding variance for some clusters in Figure 10a indicate that not all clusters meet this assumption.

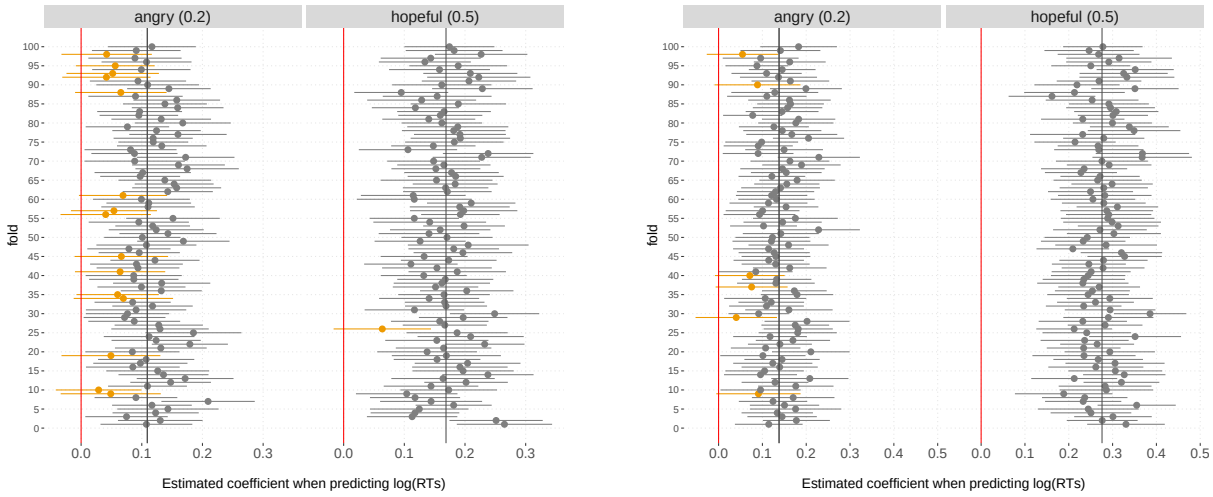
We run the following simulation in order to better understand the analytical implications of performing the label propagation for clusters with high coding variance, and so of including the images and propagated labels from those clusters in our analysis. In the simulation we investigate if taking these clusters into account get on the way of uncovering the effect of two of our 10 emotions (anger and hope) on our outcome of interest (engagements measured as the log of the number of retweets): $(Equation\ A)\ log(y) = \alpha + \beta_1 anger + \beta_2 hope + \epsilon$. First, we pretend to know the exact relationship: $\beta_1 = 0.2$ and $\beta_2 = 0.5$. Then, we pretend that the sampled images that the coders annotated are all the images in those clusters. Next we identify all the tweets containing those images and we use *Equation A* the simulate the

number of times these tweets were retweeted. Finally, for 100 folds, we sample 3 annotated images from each cluster, draw from a normal distribution to propagate the anger and hope labels to the rest of the images from that cluster (remember that we are pretending that the annotated images are the only images that exist for a given cluster), and we use the tweets conatining images with the propagated labels to estimate *Equation A*.

Figure 11: Testing whether propagation for clusters with high coding variance get in the way of uncovering known relationshiops of interest

(a) Taking into account propagated labels from all clusters

(b) Taking into accounts only propagated labels from clusters with coding variance < 5



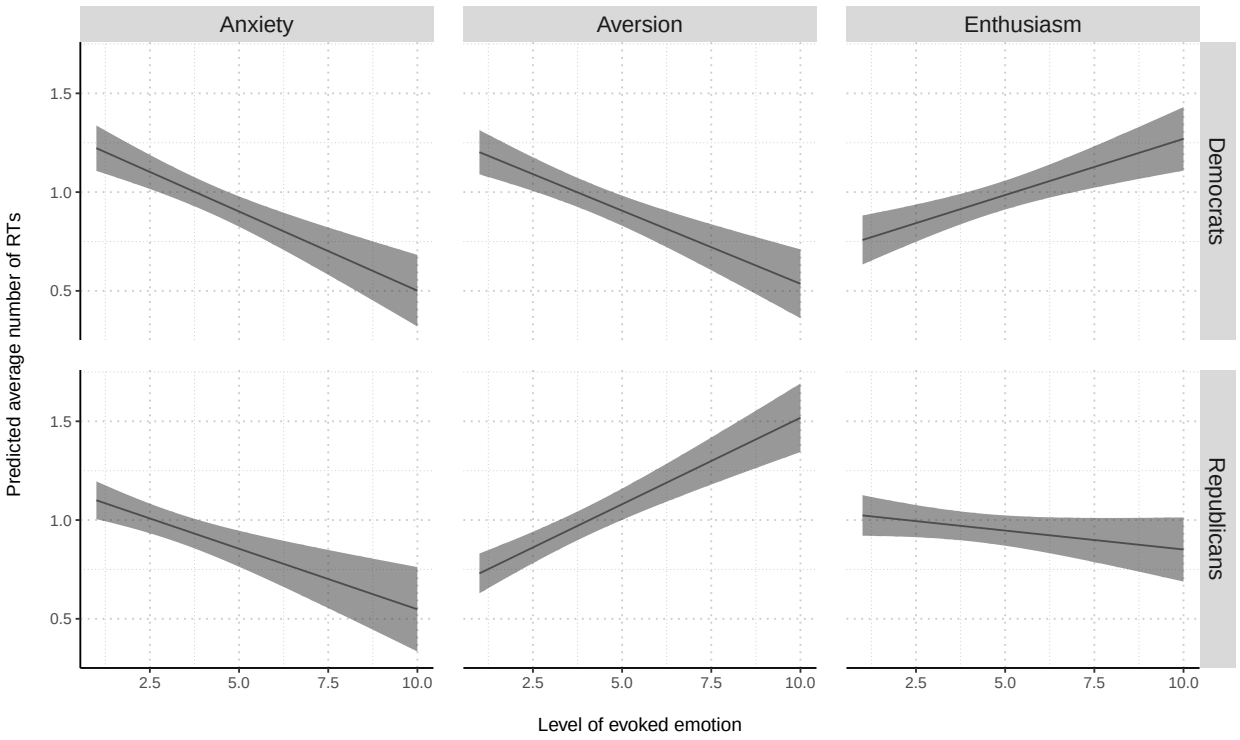
**Note:* This figure is currently based on data for 214 of the 309 clusters. We're still working on labeling the images for the other clusters.

In Figure 11 we assess the extent to which in these 100 folds we recover the known simulated relationships between anger and hope, and number or retweets (so β_1 and β_2). In Figure 11.a we show the estiamted relationship when using propagated labels for all cluster, whereas in Figure 11.b we show it when only using propagated labels for cluster with a coding variance lower than 5. We do a substantial better job at recovering the true known relationships when we only take into account tweets that have images from clusters with low coding variance. For anger, in panel (a) we estimate the relationship with retweets to be 0.11 whereas in panel (b) we estimate the relationship to be 0.14, substantavily closer to

0.2. Moreover, in panel (a) we fail to find a positive and statistically significant relationship 15% of the folds (orange estimates), for only 6% in panel (b). We see a very similar pattern for hope. In panel (a) we estimate the relationship with online engagement to be 0.17 (instead of 0.5) and to fail to find a statistically significant positive relationship 1% of the folds, whereas in panel be we estimate the relationship to be 0.28 and we find a statistically positive relationship in all the iterations.

Hence, in the final step of this showcase application we focus on the clusters with low coding variance. First, we use again a normal distribution to propagate the 10 evoked emotion scores to the unlabled images in each cluster. Then we map those image scores to all #FamilitesBelongTogeter tweets containing instances of those images and we average the scores for the emotions belonging to the same dimension in order to condense them into an enthusiasm, aversion, and anxiety dimension. Finally, we fit a linear model predicting online engagement with the movement (logged retweets) as a function of the emotions the images in those images evoked to Democrats and Republicans (enthusiasm, aversion, and anxiety). In Figure X we can see some preliminary results. As shown by previous research (Casas and Webb Williams, 2018), we see that not all kinds of images are equally mobilizing. In fact we see that those images that evoked anxiety and aversion to Democrats, and anxiety to Republicans were significantly associted to lower levels of engagement with the movements. However, we do see that in line with existing political pshychology models (Marcus et al., 2000), those visuals that evoked enthusiasm to the group more sympathetic to the movement, Democrats, were strongly associated with higher levels of engagements. We also find that those images that evoked aversion to the group less supportive of the cause, Republicans, were also associted with higher levels of engaements. This is in part because visuals that generate enthusiams to Democrats are also likely to generate aversion among Republicans.

Figure 12: Precicted relationship between the emotions images evoked to Republicans and Democrats and engagement wit the #FamiliesBelongTogether movement on Twitter



6 Discussion

Visual communication is in the rise. Finding ways of incorporating visual effects in communication and political science research is a pressing topic. However, automated methods for exploring large image corpora and for reducing the costs of annotating large datasets for the presence of complex theoretical mechanisms does not exist.

In this paper we put forward a method that aims at accomplishing both tasks. First, we use a deep convolutional neural net to represent images as vectors. Then we design an iterative k-means algotihm to cluster images into groups of very similar pictures. Next we put forward a validation procedure to find the algorithm specification that yields the best performance. After clustering the images, we show how the one can use these clusters to better understand particular parts of the data and the dataset as a whole, as well as to run

some preliminary analysis. And finally, we sample and annotate a small set of images in each cluster, and we propagate those labels to the rest of images in the cluster, lowering annotationg costs by more than 16 times without sacrificing analytical power.

As for next steps, we want to assess whether clustering algorithms other than k-means can yield more accurate clusters, extend the corpus exploration section with more illustrative examples, and explore in more detail the analytical impact of clusters with high coding variance. Nevertheless, we believe this paper will be a big contribution and enormously help those interested in studying large datsets of images in the social sciences.

References

Barbera, Pablo. Birds of the Same Feather Tweet Together. Bayesian Ideal Point Estimation Using Twitter Data. Political Analysis, pages 1–16, 2015.

Busso, Carlos, Zhigang Deng, Serdar Yildirim, Murtaza Bulut, Chul Min Lee, Abe Kazemzadeh, Sungbok Lee, Ulrich Neumann, and Shrikanth Narayanan. Analysis of emotion recognition using facial expressions, speech and multimodal information. pages 205–211, 01 2004.

Cantú, Francisco. The Fingerprints of Fraud: Evidence from Mexico's 1988 Presidential Election. American Political Science Review, 2019.

Caruana, Rich. Multitask learning. Machine Learning, 28:41–75, 1997.

Casas, Andreu and Nora Webb Williams. Images that matter: Online protests and the mobilizing role of pictures. Political Research Quarterly, 0(0):1–18, 2018.

Clifford, Scott and Spencer Piston. Explaining Public Ambivalence about Homelessness Policy: The Role of Disgust. Political Behavior, 2016.

Dahmen, Nicole S. Photographic Framing in the Stem Cell Debate. American Behavioral Scientist, 56(2):189–203, 2012.

De Choudhury, Munmun, Shagun Jhavery, Benjamin Sugary, and Ingmar Weber. Social Media Participation in an Activist Movement for Racial Equality. In Proceedings of the 10th International AAAI Conference on Weblogs and Social Media, Cologne, Germany, may 2016.

Freelon, Deen, Charlton McIlwain, and Meredith Clark. Quantifying the power and consequences of social media protest. New Media & Society, 2016.

Gerber, Alan S., Donald P. Green, and Christopher W. Larimer. Social pressure and voter turnout: Evidence from a large-scale field experiment. American Political Science Review, 102(1):33–48, 2008.

Grabe, Maria Elizabeth and Erik Page Bucy. Image bite politics: news and the visual framing of elections. Oxford University Press, Oxford; New York, 2009.

Hassin, Ran R., Melissa J. Ferguson, Daniella Shidlovski, and Tamar Gross. Subliminal exposure to national flags affects political thought and behavior. P roceedings of the National Academy of Sciences, 104(50):19757–19761, 2007.

He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep Residual Learning for Image Recognition. In arXiv:1512.03385, 2015.

Jain, Anil K. Data clustering: 50 years beyond k-means. Pattern Recognition Letters, 31 (8):651 – 666, 2010.

Kharroub, Tamara and Ozen Bas. Social media and protests: An examination of Twitter images of the 2011 Egyptian revolution. New Media & Society, feb 2015.

Marcus, George E., W. Russell Neuman, and Michael MacKuen. Affective Intelligence and Political Judgement. University of Chicago Press, Chicago and London, 2000.

Marcus, George E., W. Russell Neuman, and Michael B. MacKuen. Measuring emotional response: Comparing alternative approaches to measurement. Political Science Research and Methods, 5(4):733754, 2017.

Nelson, Douglas L, Valerie S Reed, and John R Walling. Pictorial superiority effect. Journal of experimental psychology: Human learning and memory, 2(5):523–528, 1976.

Paivio, Allan, T B Rogers, and Padric C Smythe. Why are pictures easier to recall than words? Psychonomic Science, 11(4):137–138, 1968.

Peng, Kuan-Chuan, Tsuhan Chen, Amir Sadovnik, and Andrew Gallagher. A mixed bag of emotions: Model, predict, and transfer emotion distributions. In 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 860–868, June 2015.

Poutvaara, Panu. How do candidates looks affect their election chances? IZA World of Labor, 370:1–11, 2017.

Tajfel, Henri. Human Groups and Social Categories: Studies in Social Psychology. Cambridge University Press, Cambridge; New York, 1981.

Todorov, Alexander, Anesu N Mandisodza, Amir Goren, and Crystal C Hall. Inferences of Competence from Faces Predict Election Outcomes. Science, 308(5728):1623–1626, 2005.

Torres, Michelle. Give Me the Full Picture: Using Computer Vision to Understand Visual Frames and Political Communication. 2019.

Valentino, Nicholas A, Ted Brader, Eric W Groenendyk, Krysha Gregorowicz, and Vincent L Hutchings. Election Night's Alright for Fighting: The Role of Emotions in Political Participation. The Journal of Politics, 73(01):156–170, jan 2011.

Webb Williams, Nora, Andreu Casas, and John Wilkerson. An Introduction to Images as Data for Social Science Research: Convolutional Neural Nets for Image C Cambridge University Press, New York, NY, 2019.

Won, Donghyeon, Zachary C. Steinert-Threlkeld, and Jungseock Joo. Protest Activity Detection and Perceived Violence Estimation from Social Media Images. In Proceedings of the 25th ACM International Conference on Multimedia, 2017.

Xu, Can, Suleyman Cetintas, Kuang-Chih Lee, and Li-Jia Li. Visual sentiment prediction with deep convolutional neural networks. 11 2014.

Appendix A Data Collection

To build our data set of mobilization attempts, we collect tweets that contain mobilizing hashtags used by social organizations, news media, and legislators (all based in the USA) from January 1st, 2018 to December 31st, 2018. We collect all tweets from 1,144 American social organizations, 559 American political actors, and 30 American news media outlets. We track Twitter because this social media platform has become an effective mobilizing tool for social organizations and legislators. It is also one of the most open social media platforms in terms of data sharing.

The social organizations we track were identified by the 56th edition of the Encyclopedia of Associations National Organizations of the United States (EoA), published in 2017. The EoA contains information on roughly 23,000 organizations, but after limiting our list to organizations in the "Public Affairs" subject category and manually removing inactive and removed Twitter accounts we built a list of 1,144 Twitter accounts to track (74.7% of the total population of EoA Public Affairs associations). In addition, we supplemented the EoA list of Twitter accounts with the official accounts from the most prominent news organizations in the United States and from every member of the 115th United States Congress. For news media outlets, we referenced numerous lists of the most watched and read news organizations and the most Tweeted news organizations. In total we tracked 30 media accounts and 434 accounts from U.S. Representatives and 100 accounts from U.S. Senators (some U.S. Representatives did not have Twitter accounts). Full information on the Twitter accounts that we track are available in supplementary documents.

Starting on January 1st, 2018, we began collecting all tweets produced by these tracked accounts. Although this data collection process continued until the end of June, 2019, for the sake of this paper we only use tweets up to the end of December, 2018, which gives us a full year of data. From tweets used by these accounts over this time period, we focus on the hashtags within these tweets. Hashtags are a means of organizing on Twitter, so we use this feature to identify mobilization attempts. At the end of each day we pull a list of hashtags that were used more than twice by the same tracked account. From this list, we remove all hashtags that do not have a capitalization in the middle or are shorter than 12 characters. These requirements ensure we are tracking unique hashtags that are being used prominently by at least one of these organizations. Once on our list, we immediately begin collecting any tweet by any Twitter user that uses that hashtag. Each hashtag is tracked for two days and then removed if it is not used more than twice by the same organization over the next two days. Due to the sheer number of posted tweets, we are unable to collect all the tweets using our tracked hashtags, but we are able collect around 1,000,000 tweets per day from an average of 600 hashtags. This process populates a database of tweets that use any of our tracked hashtags on the days we are tracking that hashtag.

In total, we have roughly 4 million tweets from our initial tracked accounts and around 400 million tweets collected by tracking hashtags. In addition to data from each tweet such as the tweet text, count of retweets/favorites, count of account followers, and count of friends, we also collect any pictures posted with the tweets. We do not collect videos, but we do collect the image displayed on the tweet representing the video.

From tweets from tracked accounts, we identify which of the hashtags used by these tracked accounts are mobilization attempts (either online and offline). [5].

[5] A detailed explanation of this process can be provided upon request, but it is not integral to the method being discussed in the paper