Exploring the connectivity of memes and emotions of images through the use of Tagasaurus

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Abstract

Images have proven to be catalysts of emotions and ideals at a personal level and for collectives hoping to make change. Political mobilization can be triggered and directed by images which share ideological position, and politicians can use them to signal to followers where they position themselves within the political spectrum. As content becomes easier to create and disseminate from the populace those seeking to study the images will find themselves in need of tools to improve the efficiency and organization of their work. This study presents an analysis of the datasets that the application Tagasaurus can produce. Tagasaurus, is a cross platform application for providing semantic information as annotations for images. The annotations guide the user to input descriptions for the production of hashtags, emotional variables and memes. The export facility allows a JSON to be produced for the collection of annotations and subsequently a researcher can investigate associations. Based on a dataset of over a 100 images, a set of diagrams displays the capabilities for investigating cross community meme adoption in order to see the overlaps and distinctions in the symbolism used between groups sharing content. The investigation also shows how emotions and hashtag co-occurrences can be studied.

Introduction

Understanding the images which affect the public discourse is of paramount importance (Wagner, Kronberger, and Seifert 2002) since it can help investigators make predictions about the direction of society and the aspects are of concern in the societal consciousness. Images can be powerful fueling political mobilization and triggering emotions as found in the study of (Casas and Williams 2019) which also looks into which emotions are invoked. In the effort to monitor events and provide correct interpretations many practical concerns arrive in terms of organizing the image content collected and labeling them as well. This study presents a continuation of the exploration of *Tagasaurus* (Mantzaris et al. 2021b,a) which is an application for organizing and labeling images. It takes a different approach from other semantic labeling projects such as (Qian et al. 2013) which is aimed at travellers, (Qian et al. 2014) which uses crowd sourcing, and work aimed at uncovering emotions via the use of deep learning (Minaee, Minaei, and Abdolrashidi 2021). Each approach has its merits and Tagasaurus provides a solution to aspects not addressed by other methods which may assist research in the effort to understand memes (Blackmore et al. 2000) to a greater extent. Tagasaurus provides a researcher a tool that they can use themselves, or employ others to use, in order to semantically label images with hashtags, emotions label-values and memes. This data can be visually inspected after it is stored or exported to be analyzed as a collection using other programs. With the clear distinction in attribute annotations the researcher will be able to produce networks based upon semantic overlaps in the emotion, tag or meme space that will help understand the community adoption of certain trends.

It is interesting that recent research (Xi et al. 2020) provides an understanding for how politicians can express political ideology within the public discourse via social media. That there are features in the images which differentiate one political ideology rather than another. Within a competition between ideologies these distinctions become apparent in the comparisons so that the features become motifs. This shows that a study of the images shared in political discourse can assist in detecting ideological positions in future images shared. Such work can help train automated machine learning classifiers for detecting political features as studied in (Joo and Steinert-Threlkeld 2018) where images as data is presented as an overview for the domain of political science. Much of the output tasks for the machine learning systems discussed is focused on demographic variables, group sizes and detection of police officers for instance which is important for monitoring activity from streams of images that are too many to manually follow in real time.

The importance of studying images is further reinforced from the study of (Bazaa and Bucy 2020) which discusses *nonverbal* expressions through the body language and facial expressions. This information can be lost to the researcher focusing on the direct textual production from political leaders and those representing a movement. Symbols such as an American flag and a bald eagle can promote an affiliation with patriotism (Messaris 1994). This reinforces the need to consider images as a collection components which come together to provide an ideological position within the political discourse. Much of this information can be lost or not taken into account due to practical concerns.

With many different components of images which have ideological associations it is important to find the associations as a type of correlation (Joshi and Buntain 2021) set where the different features co-occur within images provided with a certain politically identifying label. (Joshi and Buntain 2021) uses 3 different deep learning models to provide characterization labels to cluster content shared on Twitter from politicians. A vital and key aspect from this work is that it also shows that caution must be applied by researchers using machine learning on images since there is a real hazard that visually similar images can express "vastly different semantic meanings and ideological positions". Semantic information is important for training and since the images are processed as a whole the machine learning models can be assisted by being able to label the surrounding objects which indirectly participate in the key output label sought. This is especially true for memes which have many image component manipulations which participate in the semantic classification (Miliani et al. 2020).

The work of (Du, Masood, and Joseph 2020) discusses the understanding memes which is an enigmatic topic since the time that they have proliferated over the internet (Denisova 2019). There are many challenges that that must be taken into account when conducting a study of memes. In (Bauckhage 2011) a relatively small number of meme images are considered, 150, and in this way the focused research shows how the dynamics for memes with different labels can display different dynamics of spread. The different modeling parameters for the SIRS models produce behaviors characteristic of the semantic information. When considering a protocol of classifying memes (Molina 2020) provides some insight but it is a challenge as to see how this can be scaled in some way as to move from small datasets to larger ones even if in the medium sized category. This is an area where Tagasaurus aims to provide support, in easing the semantic labeling effort when the labels are missing and/or do not cover a substantial amount of the image artifacts.

Tagasaurus had an initial motivation to provide a tool which can minimize the *cognitive fatigue* encountered by professionals who must focus on user interfaces for long periods of time. This has been shown to be a serious issue for those in the nursing profession (Faiola, Srinivas, and Hillier 2015). Another issue was to provide a tool where seniors can log their emotional responses to photos and have those recorded for future references where those emotions may not be an easily accessible memory (Gose and Levi 2011). These contexts and how tagging fits into them is discussed in more detail in the original work of (Mantzaris et al. 2021b). Another use case was explored in (Mantzaris et al. 2021a) where the tool was modified to assist researchers in machine learning who are interested in training models for producing image descriptions and tags without human intervention (Gatt et al. 2018). This tool would allow users to produce annotations with greater comfort/ease while not requiring external user consent for the use of the data.

The components for Tagasaurus have been selected with the goal of minimizing the possibility of privacy infringements a researcher must take into account to avoid while studying a corpus of images. This related to the personalization paradox(Sutanto et al. 2013) where a user's input into tailoring a system can bring into question what is allowed to be distributed to a larger body, where this is stored, and if the end data can be can be analyzed in an aggregate manner so that specific views of images can be obscured. This will be important when users who look at politically motivated memes (Chagas et al. 2019) as users may act differently according to the privacy level they discern from the experiment environment of the tools they use (Aghasian et al. 2017).

The Tagasaurus application is openly available (Mantzaris 2022) on GitHub.com under the MIT license allowing free distribution and modifications by others. It is developed within the *ElectronJS* (Jasim 2017) which allows for cross platform application building (for Windows, MacOS, Linux) while it can be developed on any of those systems agnostic of the user platform. Applications such as Visual Studio Code (Del Sole 2021) are developed with the ElectronJS application build. The language used is mainly javascript for the program logic and HTML/CSS for the user interface. It can be loosely thought of as a web-application running locally on the user computer. There are a selection of different databases which can be used to store the user annotation records. The current database being used is *Indexeddb* (Kimak and Ellman 2015; Rojas 2020) which is a NoSQL database, that operates within the browser that ElectronJS uses that is Chromium (Reis and Gribble 2009). First hand experience with this database has shown that it offers easy development avenues since it is installed by default in the browser and the data can be inspected manually through the browser developer tools. Each record is identified by a single key that acts as an index and upgrades can allow for more keys from the stored JSON objects to act as indexes.

With the use of Tagasaurus is it hoped that investigators will be able to increase the rate in which manually applied semantic labels will be generated for image an corpus without inducing increased cognitive fatigue upon the person labeling. Another facility is that if provides an effective tool for organizing and arranging a collection of images obtained. The semantic information structure will also help the researcher produce networks which are very useful tools for obtaining a general understanding of the community structure underlying the spread of the content.

Data

The images were captured from the PhoMemes Data Challenge and popular websites. These images contains political protest, landscape and historical images, celebrity photos as well as popular memes (See table 1). The political images and memes were copied from the PhoMemes data challenge (PhoMemes 2022) and contained a wide scope of images and memes that were utilized in this research. The landscape images were downloaded from Pexels and PhoMemes (Pexels 2022) under the two major search areas including Caribbean Beaches and Historical Landscapes. The search results for the top photos in each areas were downloaded and uploaded to Tagasaurus using the mass upload feature. The celebrity photos were downloaded from Pinterest website (Pinterest 2022) with the latest treading photos including the Oscars, Will Smith and Prince Charles visit to Jamaica.

Similar to the landscape images these were also downloaded and uploaded in a mass upload to the tool. The meme store was created using PhoMemes (PhoMemes 2022) and Giphy memes (Giphy 2022) and the most popular memes were selected for the meme database in Tagasaurus.

A tagging test was conducted from the images and exported to the information to learn more information related to the connectivity of memes and emotions. This test was completed by sequentially reviewing the pictures and annotating the descriptions, assigning the memes and creation of the emotion scores per image. The progress was monitored with the home page scoring which contains a progress and awesomeness score.

Type	Images
Political	300
Landscape and historical	50
Celebrity	100
Memes	300

Table 1: The dataset used here in terms of the composition of the different types of images used.

Methodology

Figure 1 shows the high level view of the data extracted from the user for the image tagging procedure. The main concept from tagging is that a user can annotate an image with a description that is processed to create *tags* (akin to hashtags), *emotions* as a list of labels with values, and *memes* of which each meme can also take the role as an image. The storage of the user data per image can be seen in this map as the separation of information from a single image annotation. Over the corpus of images a set of these annotations are produced in which each component can then be compared with other annotations of the same type such as in the exploration of the variation in emotional associations with images. A an association investigation across types can be done as well where emotional interactions with tags can be tested for instance.

Figure2 shows an example screen capture of the usage of the Tagasaurus tagging interface used for this study. The correspondence with the initial wireframe design can be seen where the central images represents the object of focus for the user to produce the annotations. The right tab contains the user image description which can take free form text without constraints which is processed in order to produce hashtags. The top-left area provides the user with the ability to change the values of the emotion labels, remove labels, and add new labels. The values are currently set as a possible range in 0-100. On the bottom left is a box for the list of memes the user can associate with the central image that the user can scroll through. The user can deselect the toggle button above each meme and then upon pressing the *save changes* button have those memes removed as associated annotations for the image. Since memes can have small font text on them the meme view as thumbnails does not always suffice and the user has the option to click on a meme

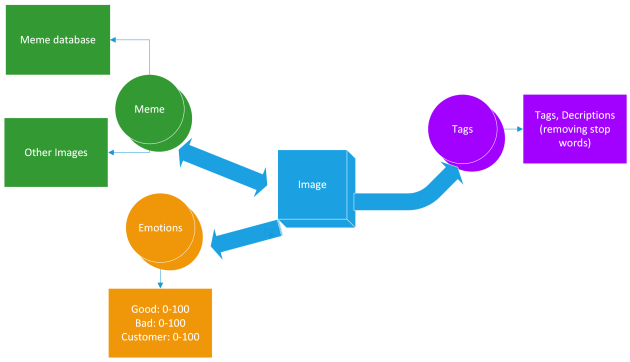

Figure 1: Presented here is a top level view of the structure of the data captured by the Tagasaurus tagging phase. Intuitively the operations of tagging can be thought of as organizing the data into the aspects of 'tags' (as in hashtags), 'emotions', and 'memes' which are provided by a single user manually.

which will produce a *pop-up modal* that shows the meme in a larger view on the z-axis with a summary of the tags and emotions that meme has itself.

As an example Figure 2 presents a popular image where there is a US protest with police. Using an image of the protest, we included descriptions, emotions of bad, fear and justice and a number of memes were associated. The image annotation provided by the user, which in this case is that of this research team, is used to make further associations with other image annotations to find where this image resides within a network view of the annotation space. The wider group of images of other political memes act as a reference for justice. This discussed in the Data section which briefly surveys the dataset of images used. We conducted an analysis of the dataset and found some interesting relationship as part of the research using this image as an example.

Figure 3 shows an example of the view that the user sees when one of the memes associated with an image is clicked on. A popup modal is produced on a higher z-axis level where the image takes a larger portion of the viewing port of the application. The top 2 rows display a list for the tags associated with the image and the emotion label-value list as well. The user can select the close modal icon on the top right or outside of the modal to return to the normal view. (Commons 2022)

Within this tagging view, the user has a set of controls from this page to continue annotating images. The *next* and *prev* buttons allow the user to cycle through images stored in the app incrementally. The user can use the *Load new images* to load 1 or more new images from the local disk space into the application. The application moves the current image focus to the new image and in the case that multiple images are selected the first of the list becomes the new focus. The application has been tested with uploading dozens of images simultaneously without problems arising. The new images are placed in alphabetical order by default. The user can also delete images from the store, and reset all of the annotation information to the default with the 2 red buttons.

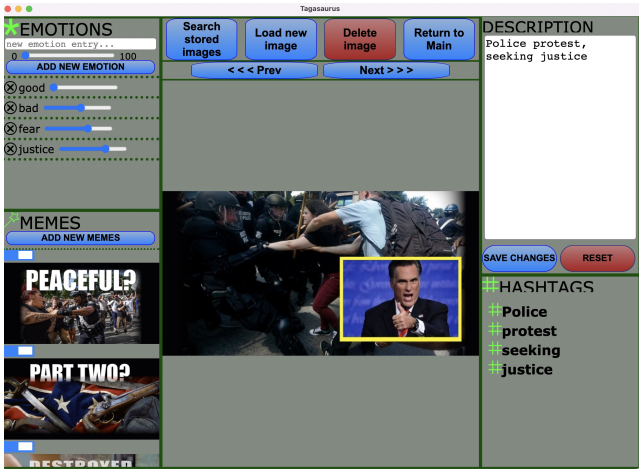

Figure 2: This is an image of a screen shot of the user experience using Tagasaurus for the creation of the image annotations produced for this study. The top right is where the user can insert a free form description of the central image, the bottom right displays the hashtags, the top left allows the user to express emotion labels with values for those emotions, and the memes can be associated in the bottom left. There are controls for the user to save changes, load/delete images, and scroll through the images stored.

Search mechanisms are allowed for the user to search for a new image order (non-alphabetical) based upon annotation information, and for the addition of memes, but since it was not used in this pilot study the search mechanism is not discussed here. For the production of hashtags from the user provided description the *stop-words* (Popova et al. 2013) are removed. There is room for improvement but for this study it is not the main focus as this corpus is not intended to be disseminated but to provide a proof of concept for the network view of such annotation data.

Given a collection of images $\mathbf{X}$ each image found in the folder read by the application by default is a collection of individual images that can be indexed over i; $\mathbf{X} = [X_1, X_2, \ldots, X_N]$. Here the number of images is N, and each image is X_i. Each X_i variable is associated with the state of the user inputs on the UI;

$$X_i \leftarrow \{\mathbf{E}_i, \mathbf{M}_i, \mathbf{T}_i\} \tag{1}$$

Where $\mathbf{E}_i$ is the state of the emotion value widgets for image i (where, $E_{i_j} \in \mathbb{R}$), $\mathbf{M}_i$ is the binary (Boolean) state of selection for the different image link associations (where, $M_{i_l} \in \{0, 1\}$ and $\mathbf{T}_i$ the set of tags produced from the description (where $T_{i_k} \in \mathbb{Z}^+$ since each integer corresponds to a unique tag keyword element). Algorithm 1 provides a basic understanding of the data entry process with the pseudocode.

This clear separation of the different variables of the annotations allows for a more direct investigation on the association of memes with emotions and tags that would otherwise be more challenging due to the challenge of separation. The work of (Murthy and Kumar 2021) discusses a set of different approaches for detecting emotion from text and in this

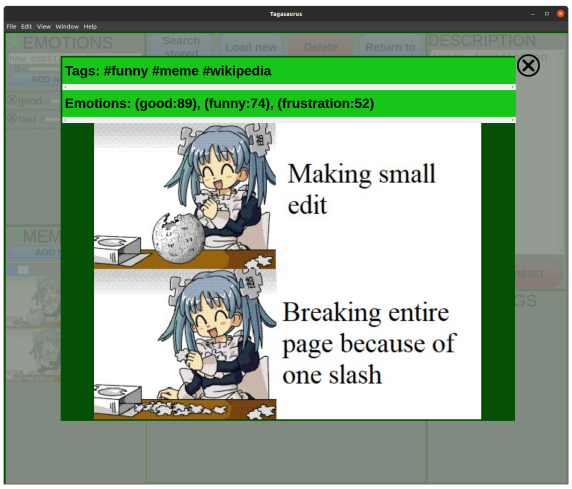

Figure 3: Presented is the view the user sees when a meme thumbnail is pressed. It creates a modal with a summary of the emotions and tags the image used as a meme contains. Image taken from (Commons 2022).

review it can be understood that certain challenges still exist with modern techniques and larger datasets as did during the time when a similar study was made (Aman and Szpakowicz 2007) over a decade prior. The nuances and context specifics (Saravia et al. 2018) make the identification of emotions to be a challenge in itself which can only add to the difficulties investigators of memes encounter in their efforts to track changes in perception towards societal behaviors expressed in memes. There are even corporate ventures such as *Oculizm* which bypass the challenges of ML for learning representation of the images for annotation by relying upon group efforts which individually aggregate towards creating a better system use case as shown in (Xu et al. 2018) for mobile sensing.

The analytics investigation will look at associations between different images from overlaps of these annotation features provided by the user. One investigation will look to produce a network, $G = \{V, \epsilon\}$ of memes which overlap in the images they each reference. That is when an image V_i takes the role of a meme for an image and another image V_j as well so that an edge is produced $\epsilon_{j,k}$. Each edge $E_{j,k}$ is produced upon the condition

$$\epsilon = \{\epsilon_{j,k}; V_j \in \mathbf{M_i} \wedge V_k \in \mathbf{M_i} \forall (i, j, k)\}. \tag{2}$$

Other investigations will look at the meme overlap network between images that can highlight where memes bring together different images. This can help bring together seemingly different concepts which are bridge spanned (Long, Cunningham, and Braithwaite 2013; Mantzaris 2014).

$$\epsilon = \{\epsilon_{j,i}; V_j \in \mathbf{M_i} \forall (i, j)\}. \tag{3}$$

After producing annotations with the tool, an export data operation is provided on the main menu, which allows the user create a JSON with all the annotation information. The JSON comprises of a collection of nested objects with a key

Algorithm 1: Tagasaurus Item Addition

AddItem(image, description, emotionscale, imageconnections)

tags = remove_stop_words(description)
emotions $\leftarrow \emptyset$
emotions[$emotionscale_1$] $\leftarrow Happy_{new}$
emotions[$emotionscale_2$] $\leftarrow Sad_{new}$
emotions[$emotionscale_3$] $\leftarrow Confused_{new}$
imageConnectionMatrix$\leftarrow$ $getDBimageConnections()$
for all i=1,2,...,N **do**
  imageConnectionMatrix$[image, i]$ = imageconnections$[i]$
end for
db_store(image, tags, emotions, imageConnectionMatrix)
return update_tagging_score($Score_T, Score_E, Score_M, Scor$

being the file name of the image. Each filename key has a JSON object property that is the annotation with the information of the annotation the researcher can use to extract. This annotation data includes:

- an array for the file names of the memes associated with the image
- the string of the raw user description of the image
- an array of the tags produced from the user description
- an array of JSONs which store the emotion label-values as key-value in a manner similar to a standard dictionary
- the hash of the file contents to exclude duplicates

Results

Figure 4 presents a network diagram where the edge set is produced according to Eq2. The images which exist as nodes are those images which have been used as memes in annotations and the undirected edges where they reference the two memes reference the same image. The network is disjoint showing how the memes can form islands of separation for the image collection from the perspective of the user who did not find memes that overlap with all the images in some way. This can allow the investigator to explore different communities based upon the meme usages.

Figure 5 shows the network of edges between images produced according to Eq 3. Here the edges are directed as the image for the annotations has edges which point to the memes that reference it. In this example 2 images are shown, one of Will Smith and the other of a beach seen. These 2 images cannot have edges directed at each other since they do not act as memes for each other. There can be an indirect association though through the use of a common meme which is a *Kermit* character. The "cool" nature of Kermit was used in the tagging of Will Smith and a beach. The other meme types include: "First World problems" signifying issues that Smith had, "Is this a...?" meme referring to a confusion as to what happened, a "Will Smith slap" meme with Chris rock, and the "Squinting woman" meme with a *tired nature*.

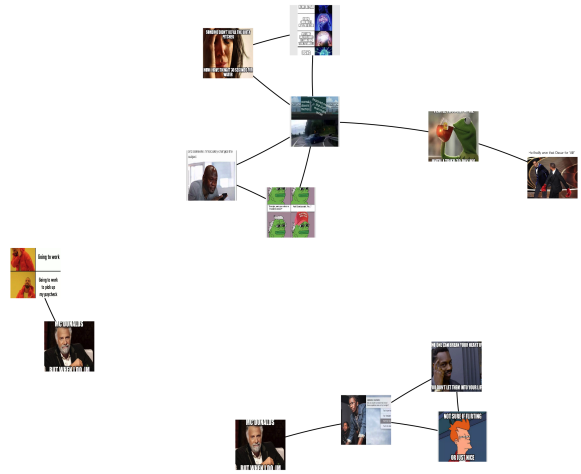

Figure 4: The disjoint network presented shows the set of edges between images which also take the role of acting as *memes* for other images. The edges are produced when 2 or more *memes* are associated with a common overlapping image. This allows an investigator to look for clusters of memes which are related to images that invoke a similar response. These edges are *undirected*.

Figure 6 shows the same type of network image reconstruction as in Figure 5, but the images used are different. The image annotations used highlight an important artifact that can appear from the usage of memes where an image that does not reside clearly within the scope of meme classification (Molina 2020; Du, Masood, and Joseph 2020) but is used as such within the context the user understands. This can therefore create within a network both directed and bidirection edges as can be seen in the diagram. In this case 2 images were used as memes for each other so that they both point to each other taking on the roles as image and meme. Although a formal classification of the images could invalidate the usage and ignore such annotations it does exist as a possibility to be observed in the datasets from users. These 2 images are from Buckingham Place and another historical landmark.

Figure 7 displays a chord diagram for the emotion associations that exist in the annotation dataset produced by a user. As each image can contain an emotion label-value pair with the labels being produced by the user and the values constrained to 0-100. The labels on each image annotation can overlap or not as the user can add labels and remove them with a variable number as well they can scroll through if the list is long. Here each chord is produced when 2 labels co-occur within the same single image annotation. The width of the cord is based upon the amount of the overlap for the number of times they co-occur as a percentage of the total number of times that label was observed. It can be seen how *great* and *fun* are connected as well as *fun* and *Good*. These association can help find indirect emotions which deliver new responses to images which may not have been

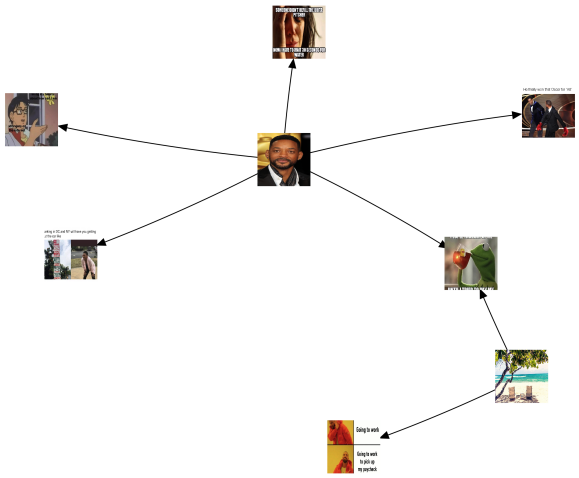

Figure 5: A network is produced of images and the memes associated with them. Each image can be associated with a set of memes connected to it with directed edges where the edge points to the meme. Multiple images can share memes which allows them to be connected. In this network diagram it can be seen how the Will Smith image connects to a meme that was placed for a beach image as well. Such diagrams helps the investigator see not only which memes are related to each other but also in respect to the images they reference.

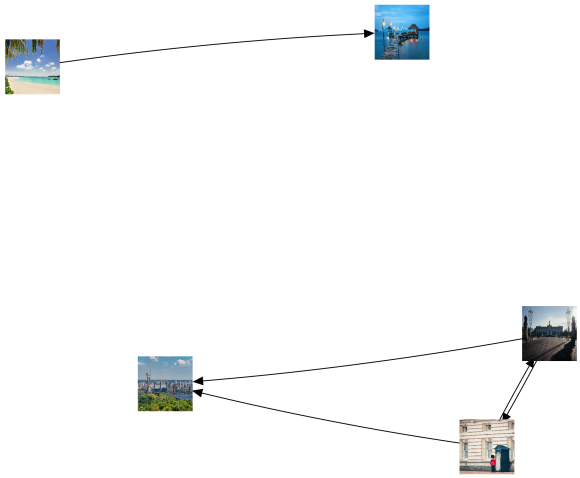

Figure 6: This diagram shows the meme an image association with a directed disjoint network diagram. The directed edges show how the origin image is a meme to the edge destination image. In the bottom right it can be seen how 2 edges in the opposite direction can be made creating a bi-directional edge which is due to each image being a meme of the other. This shows how the flexibility of the meme can produce reciprocal representations in its use as a meme and as an image itself.

foreseen, and this can be especially useful when analyzing image datasets from niche groups which have unique forms of expressions.

Figure 8 displays a network of image tag overlaps. The tags for each image annotation is produced from the description. This arc network diagram has the nodes scaled according to the number occurrences for each tag in the annotation collection, and an undirected edge is produced when 2 tags co-occur within the same tag set. The coloring of the nodes is based upon the clustering produced from this network. It can be seen how it is disjoint where isolated tag groups can exist as well as edges which span different tag *communities* as well. This can be used to find and detect community specific slang usage (Ferrer et al. 2020).

Data Challenge

The data challenge memes were loaded into *Tagasaurus* and clusters were found and are shown in Figure 9. This network diagram produced three major clusters which were classified broadly as those images pertaining to Trump, Foreign policy and protest categories. The ability to interchange photos with memes in *Tagasaurus* allows for the user to sequentially go through each image rather than have to consider the full collection. The clusters appear from the links in the meme overlaps which can then provide information for a subsequent ML training task in associating disparate labels as being associated. The clustering coefficient of over 0.6 for this analysis, and although a small network is demonstrated for the purposes of this paper display larger networks were produced. This graph was directional as if a meme or photo was associated it was classified as an edge. The value of this network provides a classification method of various types of memes into three major clusters with smaller clusters. This method of classification provides rich information into the underlying political discourse and how to provide a level of relationship between the memes in one cluster. There is also an interrelationship between the clusters of certain types which is extrapolated from similar annotated tags and commonality in the user account information. By augmenting the data with the user annotations there is bridge created between the various clusters. A small sample of user accounts associated with the clusters and tags are shown in 2. This shows that persons in one cluster may be associate memes with other clusters in the similar political forums.

The tags associated with the user accounts are shown in Table 2. This shows the clusters from the data challenge, the tags associated and the folder accounts. This shows the grouping or clustering of folder users to different political discourse. There is also interrelated clusters and folder accounts showing that persons have multiple interests in areas.

It must be noted and expected that different users can produce different labeling patterns which can change the outcomes. That is expected and the results are to be treated like that of a focus group in marketing where different archetypes are studied to find their reactions. These samples can then train classifiers for the different archetype detection from a social media stream.

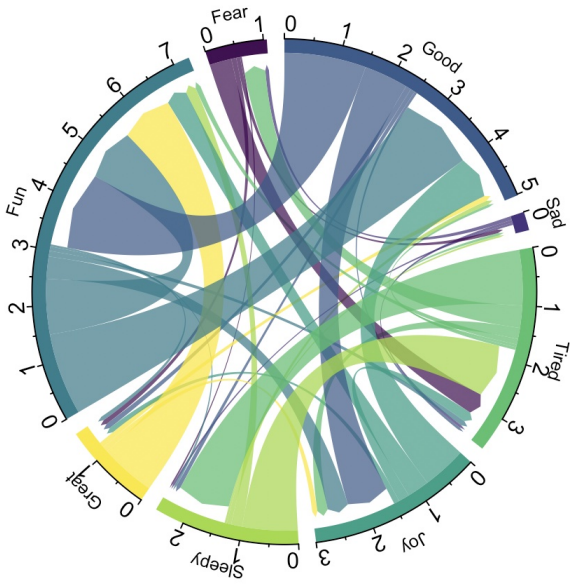

Figure 7: A chord diagram is presented to visualize the emotional label-value overlaps a user produces for the image annotations. For instance, in the diagram a yellow chord can be seen between *Great* and *Fun* since large values for the emotion *Great* in a set of images which also were present in annotations for images which contained the label *Fun*. The width of the cord is proportional to the emotion overlap percentage in each image.

Discussion

This study explores how the tool of *Tagasaurus* can be used to study semantic information applied by users when it is compartmentalized into hashtags, emotions label-values, and memes. From a relatively small collection of images, as a demonstration, an investigation shows how from the annotation export various analytics produced can be use to visualize associations between memes and semantics. A chord diagram is presented to show how associations between emotions can be examined when pairs of emotional labels are applied to the same image. This can help understand how certain emotions (to different extents) provide similar reactions.

Table 2: Cluster, Tags and Folder Account (Data Challenge)

Cluster	Tag	Folder Account
Trump vs liberal	Corruption, conservative, 2906, 3738, 215,	3282, 8442
Foreign policy	War, fear, North Korea	8612, 3815, 6622, 8498, 3738
Protest cluster police, justice	BLM, fight, protest, 8925, 2378,8612	

An arch diagram is shown for how it can depict the overlaps between the applications of hashtags produced from user image descriptions. The overlaps produce a set of edges so that a network can be inspected where community detection reveals subsets of nodes indicative of the image properties. This can be used to detect community specific terminology for image features.

With the application users can apply memes to images as an annotation component which produces a set of edges. These memes can be part of multiple image annotations linking them together producing a network/graph. The Results section here demonstrates how different networks based upon this information can be produced. A network of meme co-occurrence is produced where images which exist as memes is displayed (nodes as image thumbnails) and the edges created between node pairs when they both point to the same image. This can create disjoint networks to show meme trends that are specific to some groups whether due to them having separate sharing channels or from having distinct choices. A network is also produced where there are images displayed as nodes as well as the image memes with directed edges so that memes which connect together different images acting as bridge spanners can be identified.

Future work entails creating these annotations from a larger image set with the scope of detecting distinct meme usage patterns. Then to analyze the semantic overlaps and differences from the annotation datasets arising from 2 or more users of Tagasaurus.

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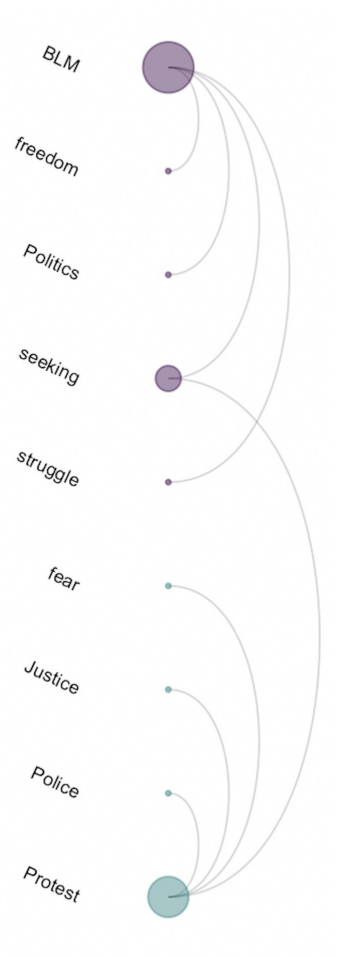

Figure 8: Presented here is an arc diagram for the overlaps and relationships between tags produced in the dataset of annotations. Each of the words exists as a tag from the user description and the thickness of the node is proportional to the number of occurrences. The edges are produced from co-occurences and the edges are undirected. The different colored sets of nodes are from the clusters produced for the tags around the images.

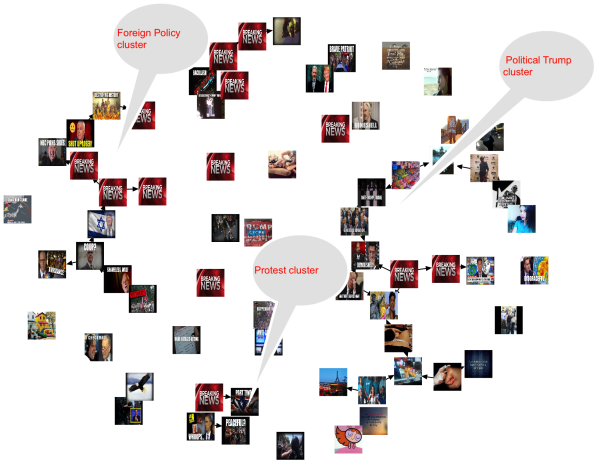

Figure 9: Presented here is a network diagram showing 3 main clusters namely foreign policy, protest and Trump cluster. There are smaller clusters of images and meme together such as for freedom, people having fun and outdoor activities. These images came from the Data Challenge. It shows how a natural clustering can arise from the tagging of the images sequentially.