A framework for interrogating social media images to reveal an emergent archive of war

Arijus Pleska
Andrew Hoskins
Karen Renaud

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A FRAMEWORK FOR INTERROGATING SOCIAL MEDIA IMAGES TO REVEAL AN EMERGENT ARCHIVE OF WAR

ARIJUS PLESKA, ANDREW HOSKINS, AND KAREN RENAUD

Abstract
The visual image has long been central to how war is seen, contested and legitimised, remembered and forgotten. Archives are pivotal to these ends as is their ownership and access, from state and other official repositories through to the countless photographs scattered and hidden from a collective understanding of what war looks like in individual collections and dusty attics. With the advent and rapid development of social media, however, the amateur and the professional, the illicit and the sanctioned, the personal and the official, and the past and the present, all seem to inhabit the same connected and chaotic space.

However, to even begin to render intelligible the complexity, scale and volume of what war looks like in social media archives is a considerable task given the limitations of any traditional human-based method of collection and analysis. We thus propose the production of a series of 'snapshots', using computer aided extraction and identification techniques to try to offer an experimental way in to conceiving a new imaginary of war. We were particularly interested in testing to see if twentieth century wars, obviously initially captured via pre-digital means, had become more 'settled' over time in terms of their remediated presence today through their visual representations and connections on social media, compared with wars fought in digital media ecologies (i.e. those fought and initially represented amidst the very chaos and scale of social media images).

To this end, we developed a framework for automatically extracting and analysing war images that appear in social media, using both the features of the images themselves, and the text and metadata associated with each image. The framework utilises a workflow comprising four core stages: (1) information retrieval, (2) data pre-processing, (3) feature extraction, and (4) machine *learning. Our corpus was drawn from the social media platforms Facebook and Flickr.*

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introduction

In the field of media studies and also war, media and memory, there is a great deal of work that tracks the role of 'media templates'.[1-3] Such templates are depictions of the routine ways that news editors and journalists refract the past by imposing visual schemas on unfolding events. With the advent of social media, and the modern tendency to post images on such platforms, we question how the presence and usage of digital media currently challenge, or reinforce, long-standing dominant means of mainstream or elite framing of war narratives. Images posted by members of the public could be amateur, professional, officially sanctioned or illicit. All contribute to an emergent *archive of war* an online 'modern media template' that continuously transforms the interrelations between the present and the past of warfare.

Our interest here is how wars fought in the digital era are shaped by their representation, reference points, and longevity or otherwise on social media platforms. In particular, we wanted to gauge how the persistence or otherwise of images of twentieth century wars, now remediated on social media, might differ to wars fought in more recent digital media ecologies (i.e. those fought and initially represented amidst the very chaos and scale of social media images).

To address these questions, we developed a workflow that enabled us to gather and analyse publicly-posted images, and the text that was posted with the images, to assess the extent and nature of emerging archives of war. We then carried out an investigation into modern war images posted on Flickr and Facebook. Our initial findings suggest that there are indeed differences between modern and older wars. Earlier war archives, such as the American Civil War, the two World Wars, and the Vietnam War, tend to be sedimented, and particularly distinct in their visual reference points. Archives of wars fought in the social media era, on the other hand, tend to comprise a more diverse and multiple blend of memories. This paper serves as a guide to our production of a series of 'snapshots', using computer aided extraction and identification techniques to try to offer an experimental imaginary of war.

research context

This work is in part provoked by Jay Winter's question, especially in relation to technological and cultural change: *What constitutes the modern archive of war?*[4] We cannot begin to comprehend this question by human methods of study in isolation.

The complexity, scale and volume of social media images prohibit unaided human attempts to arrest a meaningful snapshot of our question of 'what war looks like' on social media. Our social media analysis framework makes it possible for us to compare older and more recent war images through retrieving extensive image datasets. Crucially, the scale of these datasets can be overcome through using machine learning techniques, their recognition training being facilitated by the use of large numbers of images.

Social media provides a number of data modalities. The most prevailing ones are: visual features, textual features, and metadata. To briefly expand on each modality: *visual features* relate to image qualities such as size, texture, and colour; *textual features* relate to user comments and image descriptions; and metadata relate to date, location, and popularity. Textual user comments constitute part of social media's data architecture. Moreover, since social media is driven by user activity, the spread and richness of the content depends on the scale of user interaction. As a consequence, the content's quality can suffer from opinionated views or unrelated expressions.[5] To mitigate this, we chose to focus primarily on vision modality – images – as the main factor in comparing past and more recent images of war. This decision was informed by the challenges posed by the noisiness of the text modality. We used the vision modality to refine the text modality; that is, we established cross-modal connections between social-media instances. In other words, visual content served as the baseline for refining irrelevant textual data.

The technical issues addressed in this project include the mitigation of social media's noisiness and the homogenisation of social media's diverse data formats to support further analysis. The latter is required because social media's data access functionality is not standardised. A consequence is that every distinct mainstream social network requires the use of a bespoke information-retrieval module. For this reason, we had to develop a social media analysis module that could mine a variety of social media sources; it contained a specific adaptor for each social network being interrogated.

In addition to our aim to develop a new imaginary of war on social media, a central objective was to propose an effective workflow for supporting the application of machine learning (and other related computer science branches) to social science projects. In social media analysis, the application of such machinery is essential and beneficial since the content is vast and noisy. A human-driven assessment in isolation is infeasible because it is ineffective, inefficient and more prone to the biases of a human memory of warfare.

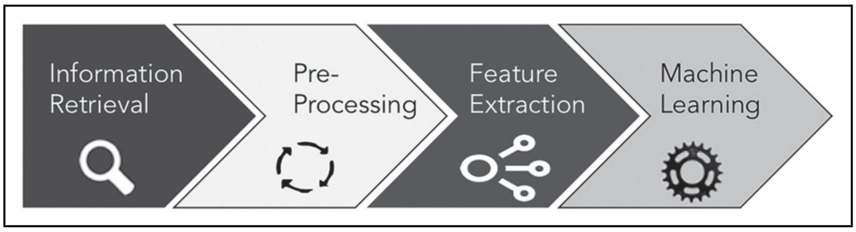

Figure 1. The Framework's Workflow Stages.

Our proposed workflow comprises the following four stages (Figure 1):

1. Information retrieval to access social media images;
2. Data pre-processing to standardise the retrieved data and eliminate irrelevant data entities;
3. Feature extraction to extract features from the images;
4. Machine learning to identify the differences between past and modern war archives based on the extracted features.

This paper is organised as follows: in the following section we provide the preliminaries describing social media's data architecture, information retrieval, data pre-processing, feature extractions, and machine learning. We then define our hypotheses and enumerate the framework objectives. Following that, we provide sources of relevant research on social media analysis. We then introduce the architecture of the developed framework. Finally, we explain our research process to demonstrate the value of the framework, before reflecting on the results and summarising the paper's contribution.

social media analysis framework

This section details the high-level architecture of multi-modal social media and introduces our framework's key constituents: (1) information retrieval, (2) data pre-processing, (3) feature extraction, and (4) machine learning.

The networked archives of social media have enabled the construction and accumulation of vast quantitative datasets. For example, there has been a trend to run workshops and competitions on finding well-performing methods to mine and explore social media, such as sentiment analysis,[6,7] detection of political spam-bots,[8] image-diversity maximization,[9] detection of topics in a sentence.[10] Social media datasets are especially useful in assessing human interaction and detecting (or predicting) events. To give a few examples, these datasets have been used to identify earthquakes,[11] assess the credibility of election predictions,[12] identify diseases,[13] as well as for surveillance.[14]

One of the key challenges in social media analysis is to ensure that the assessed content is of high quality. This means that we should be able to ensure that dataset content does indeed match the topic being studied. We refer to this as *noise refinement*. (A general introduction to the issue of social media's noisiness can be found in Postill and Pink.[15] For articles addressing the scale of the issue, see the information credibility assessments performed on Twitter.)[5,16]

Social Media's Data Architecture

Social media can be perceived as a loosely censored, globally accessible, and very active communication space. Kaplan and Haenlein,[17] for example, refer to social media as *rich* (vast and uncensored) and *intimate* (content publishers – users – can engage in informal, one-to-one interactions). Social media thus supports the modelling of large-scale, diverse human-interaction scenarios. Social network services are able to handle large scale data development, based on the data they store in their databases. Most importantly, wide ranging social networks enable and support swift and robust public data access.

Formally, we can define social media as '*a collection of posts, their attached images and comments, plus their underlying metadata'*. In Figure 2, we illustrate social media's data architecture through the example of a particular post of an image of war. The illustration shows the connection between textual and visual modalities. Note that the metadata and the noise are separated from the main part of social media (the main part is inside the large rectangle in the centre of the architecture's illustration).

Nevertheless, both metadata and noise have an impact in shaping social media war archives. That is, we minimise the noise and maximise the metadata utilisation.

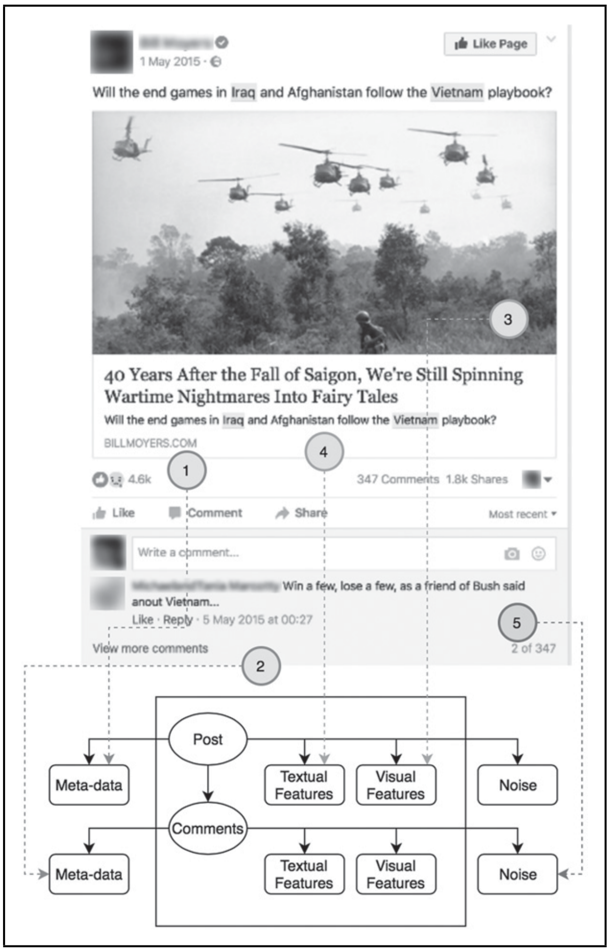

Figure 2. Social media's data architecture. Using circles, we introduce the links between the post and the proposed architecture: 1 = the post's meta- data – 'likes', comments, shares; 2 = the comment's metadata – date and user id; 3 = the image attached to the post; 4 = the post's description; and 5 = the noise in the comment (some words in the comment are irrelevant with respect to the context).

(1) Information Retrieval

Information retrieval, as the name suggests, targets social media data-query and data-access techniques. In our project, we employed information retrieval to deal with the following aspects: (a) swift information look-up; (b) identification of data modalities; and (c) retrieval of multi-modal content. Note that well-established social networks provide access to public data via Application Programming Interfaces (APIs). Essentially, APIs allow a researcher to extract data to construct multi-modal datasets. These can support both quantitative and qualitative inquiries.

The main challenges with the use of APIs are (1) rate limits, and (2) unique configurations. By 'rate limits', we refer to the way social networks limit requests to a pre-set number per day. 'Unique configurations' refers to the fact that each and every social media platform has its own way of interrogating their data store. There is no widespread convention that is followed by social media platforms in developing their outer facing API.

To mitigate the constraints of rate limits, we identified social networks with higher rate limits to support our investigations. And any social media analysis workflow requires a number of information-retrieval modules: one for each social network API.

In designing our information retrieval module, we ensured that the history of the data queries across all platforms was preserved during the search process. In this way, we ensured that we kept track of the continuous narrative development. This helped us to avoid retrieving duplicates.

(2) Data Pre-Processing

The role of data pre-processing is to organise the retrieved social media data gathered during the previous stage. We thus organised the retrieved data by imposing a standardised data format onto data collected from all different platforms. The retrieved data is stored following a formatting convention to reduce the complexity of data management within the framework. The standardised data format also makes it possible for us to dismiss a large proportion of irrelevant metadata so that we can maintain a cleaner and more manageable data set.

A local database's storage potential cannot compete with the storage capacity of a social network service. We thus had to engage in a trade-off between storing richer and weightier data of a reduced number of data points, or reduced and lighter data of more numerous data points. Our standardised and sustainable data format was designed with this purpose in mind.

To summarise: first, we separated the data modalities: textual, visual, and metadata content. Second, we elided irrelevant data fields to reduce noisiness. Finally, we preserved the unique identifiers (ids) of the social media instances in the form of our own database indices to ensure that we did not retain duplicates.

(3) Feature Extraction

During this stage, we processed the social media instances and flattened them to a set of features. To assess which features to extract, we tested their performances in the succeeding machine learning step. This procedure is known as feature selection.

It is important to be aware, once again, of the trade-off between the entropy and computational cost of feature-extraction methods. Some state-of-the-art features could be too computationally costly to process without substantial and expensive computing power. Other, more basic practical features are cheaper to extract and worked well enough to serve our core purpose.

In particular, our feature selection was informed by the types of features used in similar research projects (see 'Methodology' below). However, putting the notion of using conventional features aside, a common feature selection method would be cross validation. This entails the collection of a variety of different features, and then a check on how well the succeeding machinery performs with respect to, say, time and classification. Based on this outcome, we can identify the best-performing features.

(4) Machine Learning

In simple terms, machine learning can be defined as *an application of machinery which draws well-defined conclusions based on numerous aspects (features)*. We deployed machine learning methods that are used for classification. We began with *supervised-learning methods*. The main characteristic of these is that the first step is to train the data classifiers. To this end, we trained the classifier by using some initial data instances that have already been classified (by humans, for example). The supervised-learning classifiers then use this learned intelligence to predict the class of a data instance of unknown origin. Machine learning classifiers are admittedly error prone. The error rate could be influenced, for example, by the quality of the training data. For this reason, we introduced two metrics to assess a particular classification's performance:

(1) precision and (2) recall.

a) *Precision* is the ratio between correctly-assigned and correctly-assigned-plus-incorrectly-assigned instances of the assessed class.
b) *Recall* is the ratio between correctly-assigned and the total number of class instances.

The performance is identified using the training data (i.e., labelled data, by labels we refer to an instance's classes). For example, we would pick two different machine learning classifiers; split the labelled data into two groups: for instance, 20% is used for training and 80% for performance evaluation. Based on the observed performance, we picked the superior classifier to enable future predictions (the unlabelled data).

statement of problem

Our key hypothesis is that:

'Computing science aided analysis can inform new understandings of how wars of different eras are represented though images on social media'

To test this claim, we:

- Set up a practical machine learning module for classifying images of war with the best possible performance; and
- Incorporated metadata and textual content to reduce the noisiness of the pure image classification.

And, in addition. we:

- Devised an information-retrieval module combining several social-network APIs;
- Devised a data-pre-processing module inducing a standardised social media's storage format;
- Introduced a workflow framework that combined the information retrieval, data pre-processing, feature extraction, and machine learning modules.

relevant research

War, media and memory are intricately entangled through the contemporary memory booms[18] or turn to memory with an increasing premium being placed on the remembrance of warfare in modern societies[19]. More recently, the astonishing connectivity of the digital era delivers the unfolding of a user-oriented 'participative war[20]' through an imploded battlefield. But at the same time, the rapid accumulation and emergence of all of wars' pasts on social media contribute to a new paradigm of '**radical war**'; this is a battle over data and attention, for legitimacy and control, in which all sides are deeply enmeshed in war's digital fabric.[21] Our work seeks to provide some kind of experimental avenues for the exploration of these claims as to the persistence or otherwise of social media images of wars fought in contrasting media ecologies.

The issue of social media's noisiness can be approached using link analysis. Essentially, this is employed to discover both cross- and inter-modal feature matchings. Since social media can be interpreted as a network, a convenient way to apply link analysis is to use graph theory techniques (for an introduction to other techniques, see Agichtein *et al.*[22]). There are several examples of the application of link analysis. For instance, McAuley and Leskovec[23] used a graph to compare metadata utilisation for noise reduction in image classification. Gao *et al*.[24] refined (parsed) the text modality and applied a graph to link the resulting textual features with images. In another study, Gao *et al*.[25] quantified the strength of the text-to-image links. Denoyer and Gallinari[26] used a similar idea on link strength to rank social-media instances in order to obtain least noisy data among top-ranking results.

Apart from noise reduction, link analysis can be also useful in effective database management. De *et al*.[27] used a graph to induce a local look-up system that is based on nearest links. Such a system can be helpful when searching through a large local database. Furthermore, Wang *et al*.[28] proposed to use link analysis for extending small datasets. Essentially, if a particular class of data has an insufficient number of instances, their nearest links would be used as proxies. In our exploration of social media instances, we employed several classic machine learning methods. Again, the research literature provides good guidance.. Guillaumin *et al*.[29] extended the method of multiple kernel learning to utilise several modalities for image classification. Furthermore, Becker *et al*.[30] proposed a clustering algorithm which is specifically tailored for multi-modal content. Regarding the state-of-the-art of image classification, the prevailing methods follow the rationale of the neural network proposed by Krizhevsky.[31] A useful way to improve neural networks is through generative adversarial networks proposed by Goodfellow *et al.*[32] These could be used as is, with reinforcement learning (the rationale of reinforcement learning is based on the models that learn from their mistakes). An example of such a generative adversarial network is introduced by Yu *et al.*[33]

methodology

In this section, we introduce the methodology and the strengths and limitations of our model. Note that we present each of the workflow's steps separately and expand on the details of the chosen methods.

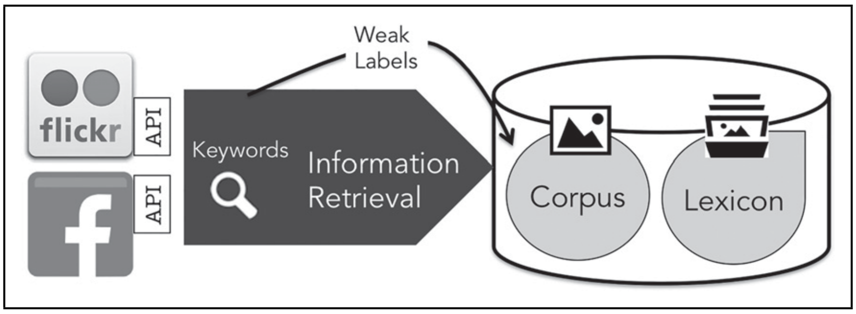

Figure 3. Information Retrieval

Furthermore, we provide a Python implementation of the application in the form of a GitHub repository*.

Information Retrieval

The workflow's information retrieval layer has two modules: one for corpus retrieval and another for lexicon retrieval. The corpus is exploratory content retrieved from social network APIs. In simple terms, a corpus is a collection of images (and their metadata). We use this to achieve war archive comparisons.

The lexicon is a collection of content retrieved from domain specific sources. The collection serves as the baseline of features that reflect the classification target (e.g., a lexicon could, for example, be a Wikipedia article on the Iraq War). To summarise, we use a lexicon to train machine learning classifiers. We then deduced the underlying classes of some assessed corpus's instances, such as social media posts.

As suggested previously, we focused on utilising supervised machine learning models. Bearing this in mind, note that we pre-label the instances of a corpus using the keywords used during the information retrieval. In more formal terms, such labels are known as *weak* labels: those used to establish a primary notion of the meaning of exploratory data. As a side note, when we use keywords (weak labels) to retrieve data, social network search engines carry out initial data refinement. Of course, the performance of their refinement depends on the algorithms behind the engines that, for the sake of brevity, we do not expand upon in this paper.

Since social network APIs are subject to rate limits, we attempt to minimise the API calls by identifying optimal query keywords. For this reason, we establish a unique and concise set of keywords for each target class of interest.

* https://github.com/perdaug/iow

As an example, the Iraq War class, which, for now, we denote as C_{Iraq}, could be associated with the following set of keywords:

$$C_{Iraq} = \{\text{`}ShockandAwe\text{'}, \text{`}SaddamHussein\text{'}\}.$$

Note that in our experimental settings, we would expand the set of keywords to incorporate more associations. However, associations that are too generic or uncommon would increase the retrieved dataset's noisiness by polluting it with irrelevant data.

In some cases, a use of diverse query keywords would return social media duplicates. For this reason, we indexed our local database i.e. deploying local identification numbers (IDs). By keeping a track of the IDs, we can easily check concurrent data feeds and thus we updated our local database only if there were no matches already stored. Furthermore, tracking the IDs enabled us to manage the database more effectively.

Data Pre-Processing

In our application settings, the main intention of the data pre-processing step was to standardise the content retrieved from different social network APIs. In most cases, the retrieved social media is in a JSON file format. JSON files include data fields with relevant textual content, links to access visual content, and a range of metadata instances. However, the JSON file structure is different for each social network. For this reason, our data pre-processing module was developed to identify the important content fields independently. Afterwards, the module outputted the results in three separate modalities:
(1) textual content, (2) visual content, and (3) metadata. Most importantly, the format we use to we store each of the three modalities is standardised.

We also used the data pre-processing step as a preparation for feature extraction, as follows:

Regarding *textual content*, we concatenated a social media post's descriptions and comments. We then stem the resulting text. By stemming, we refer to the procedure which reduces words to their morphological roots. Essentially, the stemming procedure reduces the size of the vocabulary (i.e., the number of unique word instances) and also matches the social media instances possessing similar meaning. For example, consulting, consultant, consultants, and consultative, all have a common root: consult. Reducing all of these to the root is the process of stemming.

Regarding *visual content*, we extracted images with a usable resolution for the next – feature extraction – stage.

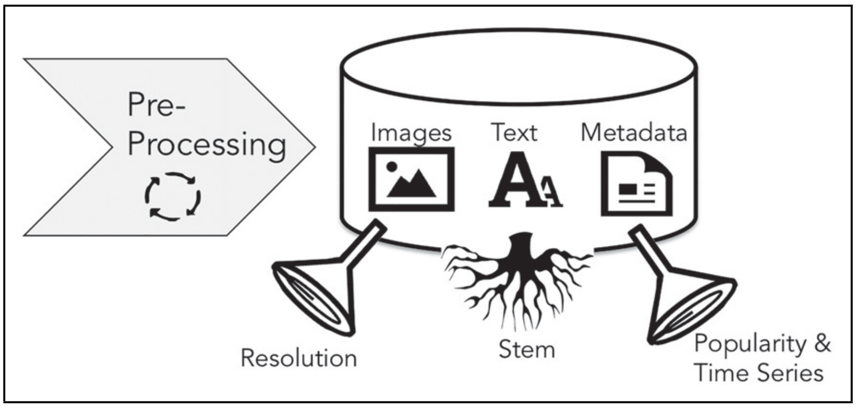

Figure 4. Pre-Processing

Finally, in terms of *metadata*, we preserved the notion of a social media post's popularity (e.g., likes) and development over time (e.g. the time stamp of comments).

Feature Extraction

In the previous subsection, we considered the data format used for feature extraction. Features are interesting points on the object that can be extracted to provide a 'feature description' of the image. Features are detectable in the image irrespective of differences in size, noise, rotation and illumination.

Here, we introduce a rationale for selecting superior features. If the number of identified prospective features is high, cross validation could be used to select well-performing features. To provide an example of how cross validation works, assume that we have three types of visual features: scale-invariant feature transform (SIFT), hue, saturation, value (HSV), and red, green, blue (RGB). Notice that, in total, there would be seven different feature combinations to choose from, namely: SIFT, HSV, RGB, SIFT + HSV, SIFT + RGB, HSV + RGB, and SIFT + HSV + RGB. Essentially, in cross validation we would perform classification over each feature combination and thus obtain performance diagnostics. It is important to note that too large feature combinations would cause computational inefficiency and issues associated with overfitting. *Overfitting* is a side effect when machine learning modules are over-influenced by training data. For instance, one possible cause is overlapping features. As a result of overfitting, the impact of unique features, which effectively deliver the most valuable information, would become negligible.

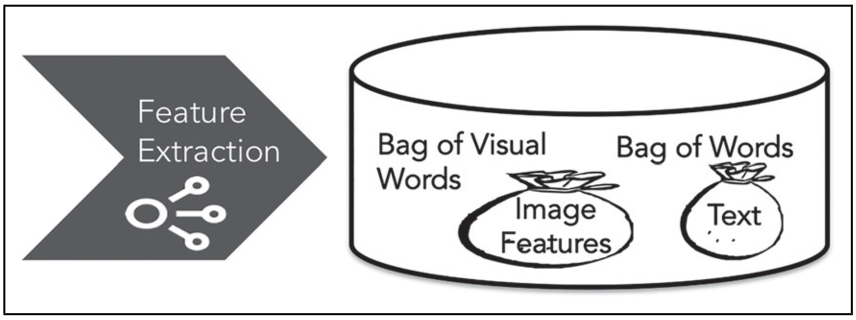

Figure 5. Feature Extraction.

Furthermore, for the sake of brevity, we assume that our textual content is exchangeable. *Exchangeability* refers to the fact that we can neglect word order. For instance, the first and last words of some text instance would have equal prior importance whereas, as suggested by some style guidelines, crucial information is often introduced at the beginning of a sentence. Furthermore, when extracting textual features, we consider each word individually (a formal term for that is 1-gram setting). As a result of the induced exchangeability and 1-gram setting, the impact of syntax upon a succeeding machine learning application is neglected. Even though some information was lost, our project settings became simpler. Also, note that the induced exchangeability and 1-gram setting can be referred as the principle of the *Bag of Words (BoW)*.

Going into the details of textual content's feature extraction, we utilised the term frequency–inverse document frequency (*tf–idf*) transformation. Most importantly, the *tf–idf* transformation refined the textual content by dismissing frequently used words. To introduce textual-feature extraction used in our project setting, we:

1. Constructed the vocabulary of the words;
2. Calculated the word counts of all word instances;
3. Applied the *tf–idf* transformation on the word counts;
4. Dismissed the words above and below some pre-set *tf–idf* thresholds.

To expand: in the first step, from the retrieved corpora (content) we constructed a vocabulary of all word terms. Next, we used the vocabulary to initialise a data structure for storing word counts (as an example, such a data structure would have the number of rows equal to the number of the content instances and the number of columns equal to the number of vocabulary terms). In the third step, we apply the *tf–idf* transformation to the stored word counts. And, finally, we set the upper *tf–idf* bound to dismiss common words and the lower *tf–idf* bound to dismiss rare words.

Regarding the details of visual content feature extraction, we focused on preserving the notions of colour and shape. The notion of colour could be perceived by hue, saturation, value (HSV) descriptors, and the notion of shape could be perceived by scale-invariant feature transform (SIFT) descriptors. It is also important to note that to assess the similarity among HSV descriptors, we can simply calculate the respective chi-squared distance (a lower distance indicates a higher similarity). This means that the design of HSV descriptors allows to skip the workflow's machine learning stage. Regarding SIFT descriptors, these do not possess such design for evaluating the distance. Therefore, to utilise SIFT descriptors, we :

1. Initialised the K-means algorithm using the SIFT descriptors;
2. Initialised the vocabulary for the visual words;
3. Calculated the word counts;
4. Appled the *tf–idf* transformation on the word counts;
5. Dismissed the visual words above and below some pre-set tf–idf thresholds.

By the K-means algorithm, we refer to a clustering method. Essentially, the K-means algorithm initialises the *K* number of clusters (e.g., 1000) and optimises the position of each such cluster with respect to the SIFT descriptors. This is the introduced procedure's first step. In the second step, we used the number of the *K-means* clusters to initialise the vocabulary for the visual words (similarly as for the previously discussed text vocabulary). Next, we obtained the word counts by calculating the distance between each SIFT descriptor and K-means cluster. Finally, in the fourth and fifth steps, the procedure is identical to the one used for textual features. Note that such treatment of visual features could be referred to as the principle of the *Bag of Visual Words* (*BoVW*).

machine learning

At this point, we introduced machine learning model selection. Firstly, we set a clear distinction between training and exploratory data: training data already possess class associations (labels) thus, training data is the evidence based on which our classifiers can predict classes; and exploratory data is the data to be assessed (it does not yet possess class associations). On model selection, note that different machine learning models are based on a different rationale thus their predictions differ; also, note that even the same model could make different predictions based on the internal parameter settings (these parameters are known as hyper-parameters). To identify well-performing models, we carried cross validation (in the similar manner as previously discussed upon addressing feature selection). Note that cross validation can be also carried to choose the hyper-parameters.

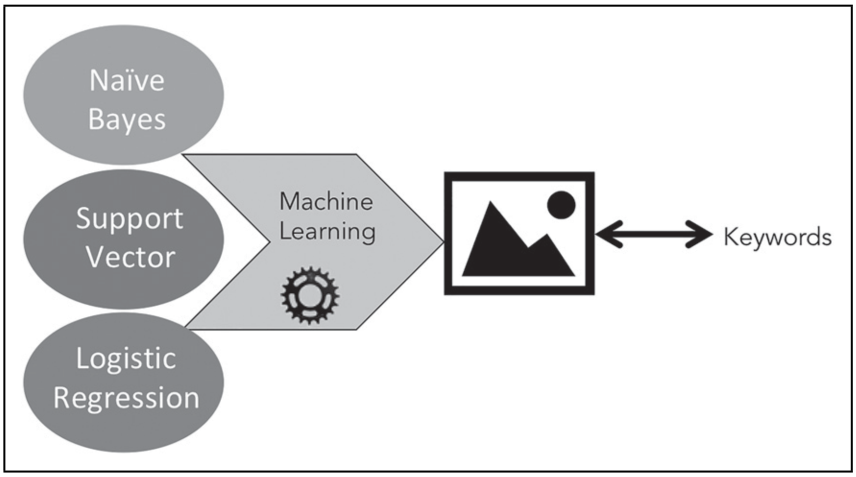

Figure 6. Machine Learning.

In the comparison of recent and past war data we limited ourselves to the analysis of one-to-one comparisons. By a one-to-one comparison, we mean that the prediction would be limited to one class. The significant part on which we based the comparison analysis is in associating exploratory data with weak labels (these are the query words used upon utilising social-network APIs). Concurrently, the exploratory data is classified based on the training data. Finally, we compared the weak labels and the predicted labels to identify if there is any difference (if there is, we interpret this as a correlation).

In relation to performance, we used the previously introduced precision and recall metrics. Note that we interpret these metrics differently for training and exploratory data evaluations. Training data, precision and recall metrics show us how well we chose, say, training instances, machine learning classifiers and their hyper-parameters. For exploratory data, low precision would mean that the class (for example, the Vietnam War) is often associated with other classes and a low recall would mean that the class possesses many associations to other classes.

For the classifications based on both textual and visual features, we used classic machine learning models. To be specific, in our assessment of past and more recent war comparisons, we performed the classification using the following models: (1) naïve Bayes,[34] (2) support vector machine,[35] and (3) logistic regression.[36] For exploratory data analysis, we selected the model showing the best performance in training data. Regarding the implementations of the models, we employed a Python library, sklearn (version 0.18.1). We explain how we utilised these models in the next section on performed experiments.

Table 1. The numbers of the assessed social-media images.

	WW1	Iraq	WW2	Syria	Ukraine	Vietnam
Facebook	13348	8746	4064	10455	8342	24893
Flickr	4384	4375	4475	4481	4416	4451

experiments

We carried out three experiments to test the viability of the Framework's workflow in comparing more recent and older images of war and to introduce some examples of how to maintain the workflow's effectiveness. The experiments were carried on data retrieved from Facebook and Flickr. Facebook contained more textual data (comments) and Flickr contained more visual data (images). Note that we trained our machine learning module using data from Wikipedia (as a point of reference for textual data) and ImageNet[37] (as a point of reference for images).

Experiment I: using textual features to reveal differences in images used to frame more recent and older wars.

We retrieved social media instances with image attachments (the numbers of the selected instances are given in Table 1). Then, we trained our classifiers using Wikipedia's data on six assessed classes. Finally, we drew a comparison based on recall and precision performance metrics, which were introduced in the Methodology Section (Machine Learning). The details of the findings are illustrated in Figure 7.

Experiment II: incorporating visual features

The second experiment utilised visual features. We used HSV descriptors to display noise refinement and SIFT descriptors to introduce the rationale of feature/model/parameter selection. In this experiment we used iconic images of war classes, for example, Nick Ut's 1972 photograph of Phan Thị Kim Phúc also known as 'Napalm Girl', fleeing severely burnt from a South Vietnamese Napalm bombing attack in the Vietnam War. Also, instead of classification, the machinery application ranks instances based on similarity. That is, we looked for the exploratory data instances that would match the iconic images. Note that we use HSV and SIFT descriptors to rank images based on colour and shape similarities, respectively. Essentially, we use HSV descriptors to induce the monochrome-image filter (with the intention to identify old, uncoloured images), whereas SIFT descriptors are used to identify images with iconic objects (e.g., the fall of the Saddam Hussein statue). More details on SIFT and HSV descriptors can be found in the

Methodology Section (Feature Extraction).

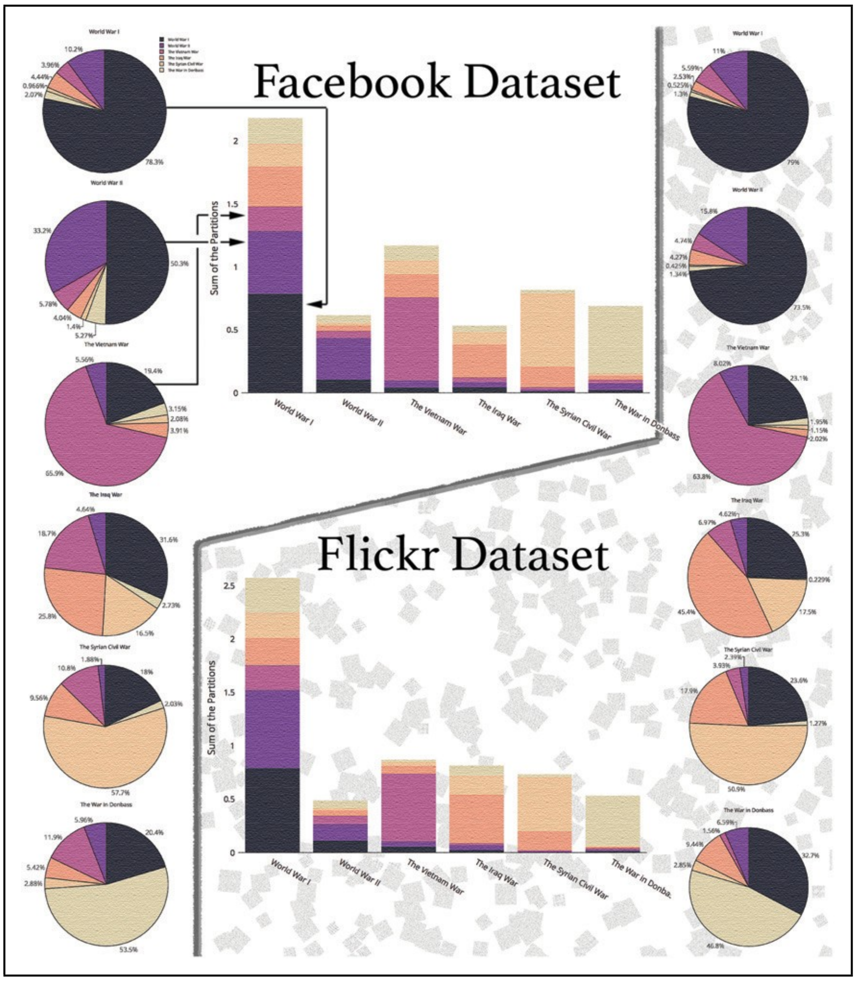

Figure 7. The identified past and contemporary war comparisons. The performance based on the recall metric in illustrated by the pie charts. Note that a single pie chart corresponds to a single retrieved dataset on a given class. The chart's segments show which other classes were identified as correlations. For example, in relation to the Facebook data: based on Table 1 above, 13,348 images were retrieved using the keywords associated with the First World War class. Looking at Facebook's pie chart, 78% of the instances remained in the same class, 10% were assigned to the Second World War class, and the margins were assigned to the remaining classes. Furthermore, the performance based on the precision metric is illustrated by the bar charts. The bar charts show which war classes were most often predicted by the utilised machine learning classifier. For example, the First World class contains 78% of the First World War's class assignments (as shown by the respective pie chart); 50% of the Second World War class instances, around 19% of the Iraq War class instances, and so on.

Figure 8. A comparison between filtered and unfiltered data. On the left, we show the top 24 results of the monochrome-filter application on the exploratory dataset (the Afghanistan dataset) retrieved from Facebook. On the right, we show 24 randomly drawn images from the same dataset. Note that the left contains more instances that are clearly war associations.

Experiment IIa: an example of noise reduction using HSV descriptors

We now introduce the rationale of the noise-reduction technique utilising HSV descriptors. Firstly, we took a set of monochrome iconic images (e.g. the set's instance could be the Napalm Girl image). We then used this set to extract the benchmark HSV descriptors. Afterwards, we took our exploratory data and extracted the respective HSV descriptors. Finally, the exploratory data's descriptors were compared to the benchmark descriptors and then ranked based on the closest similarity. The results of this process are depicted in Figure 8. Note that the monochrome filter was a convenient technique with respect to our project's settings because we were looking for images from the past.

Experiment IIb: an example of parameter tuning using SIFT descriptors

Regarding SIFT descriptors, we used these to rank images based on similar objects. The key characteristic of SIFT descriptors is their ability to identify similar objects despite distorted size, angle, or sharpness. The SIFT application's rationale differs from the HSV application's in the way that SIFT descriptors are clustered using the K-means algorithm described in Methodology Section (Feature Extraction). For our feature-selection experiment, we used 11 different iconic images. We injected 10 distorted copies of each iconic image into the exploratory dataset. For our results, we assessed how many copies of these were found in the top 100 results, based on different feature-extraction parameters. The feature-extraction parameter of our assessment is the value K of the K-means algorithm's clusters (the value K corresponds to the number of visual words). We expected that the ranking performance would differ with respect to different K values. In Figures 9 and 10, we display how many out of 10 injected images were found for each assessed value K and iconic-image class.

Note that some of the injected images could not be found using any value of K. For this reason, we normalised the findings. Normalisation works as follows: for each iconic image, we established the maximum number of injected iconic image identifications. Then, throughout all K values, we appled these maximum numbers as divisors. The normalised performance is depicted in Figure 10.

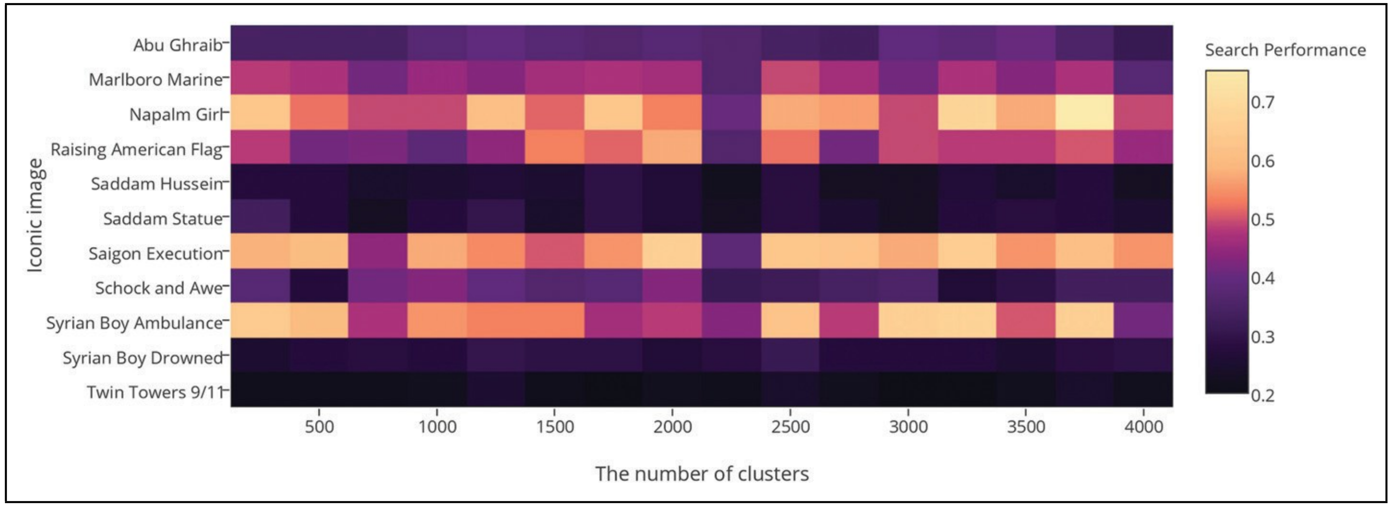

Figure 9. The search performance corresponds to the identified injected images in the ranking's top 100 results. To be specific, the search performance is the percentage of identifications (expressed as ratio). 0 corresponds to 0% and 1 corresponds to 100%.

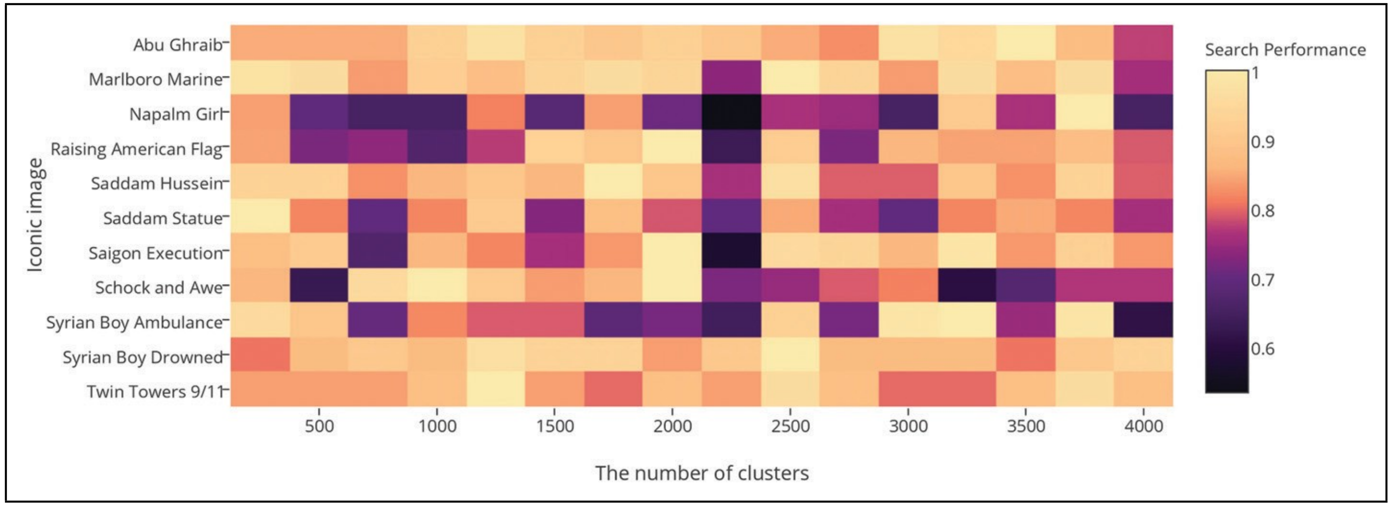

Figure 10. The normalised search performance. We found that the maximum number of identifications corresponding to the Napalm Girl is 8 out of 10 for K = 3750; then, we divide the Napalm Girl row's elements by (.8) and thus obtain the normalised performance.

Figure 11. 32 randomly chosen images classified by the workflow with Nuclear War class associations.

Experiment III: an example of noise reduction using a neural network

For this experiment we applied a neural network to extract images with Nuclear War associations from two datasets that were retrieved from Facebook and Flickr. Compared to the previous noise reduction experiment, where we used HSV descriptors, this one differs in the sense that we refined more specific/less general classes of images. For the neural-network implementation, we used a Caffe implementation of the Inception-BN model.[38] Note that this implementation is already pre-trained on the ImageNet dataset with 21,841 classes and 14,197,122 images. In that implementation, the authors report that, in their practical settings, they performed nine training rounds, each of which took 23 hours.

To introduce the settings in which we applied the neural network, we retrieved 32,630 and 4,335 image instances from Facebook and Flickr, respectively (the instances were retrieved using keywords tailored to refer to 'Nuclear War'). It was convenient that the ImageNet dataset, on which the neural network was trained, possessed labels based on which we could identify the relevant images (e.g., bombs, explosions, radioactive clouds).

After the neural network classified the datasets, we extracted the image instances that possessed the relevant labels among the top five prevailing classes. We found 169 and 62 images meeting the latter criteria (out of 32,630 Facebook and 4,335 Flickr images, respectively). A sample of the results is illustrated in Figure 11.

conclusion

This paper outlined some experimental computing science work to provide some insights into how wars of different eras are represented in images in social media. We used four key stages to this end: (1) information retrieval, (2) data preprocessing,(3) feature extraction, and (4) machine learning.

We undertook the following: data comparison based on textual features (Experiment I); broad-range image filtering (Experiment IIa); narrow-range image filtering (Experiment III); and parameter tuning (Experiment IIb).

Using these computer aided extraction and identification techniques, our collaboration has provided initial visual snapshots in offering an experimental way to conceive of a social media based visual imaginary of war.

Our initial findings suggest that, as we may expect, earlier (twentieth century) wars are more sedimented and distinct in their social media image references, compared with wars fought and initially captured in the flux of more recent digital media ecologies.

The pursuit of this avenue of this work could transform how we might interrogate how the relations between different generations of war and media are shaped, retained or lost in social memory. To this end, it is important to conceive of social media as holding and losing a radical ‘new memory[39]’, that is the most significant, yet least understood, emergent archive of warfare of our age.

ethics

We harvested only publicly posted images on these websites. We did not collect any personal or identifiable data about those who posted images.

appendix

Technical terms used in this paper:

API: Application Programming Interface. This is a kind of protocol, which specifies exactly how a developer can request information from the platform. So, for example, Twitter allows searches for a specific keyword, or to request for all of a specific individual's tweets, or to ask to monitor specific kinds of tweets as they are posted.

Corpus. Exploratory content retrieved from socialnetwork

JSON file format. A lightweight data-interchange format that is easy for humans to read and write and also easy for machines to process.

SIFT: Scale-invariant feature transform

HSV: hue, saturation, value – a colour model that closely aligns with the way human vision perceives color-making attributes.

RGB: An additive colour model in which red, green and blue light are added together in various ways to produce a range of colours. The name of the model comes from the initials of the three primary colours, red, green, and blue.

end notes

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