Digitally-assisted iconology: A method for the analysis of digital media

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Abstract
Exploring medium-to-large datasets of social media imagery can be challenging. This paper describes a digitally-assisted iconology, a hybrid methodology that includes machine learning and data analytics for sorting through medium-sized datasets of images that lack metadata to describe their pictorial content. The method plays to the strengths of current digital technologies. Using machine learning, pictures are first clustered in a preliminary stage based upon basic formal presentational characteristics. Thematic analysis follows this preliminary stage, based upon an expansion of Aby Warburg’s “pre-coined expressive values”, which are frequently found in pictures displaying high levels of user reception. Once clustered via these two separate stages, the researcher can then drill down using familiar forms of visual analysis to explore how similar concepts have been rendered in different ways. The analysis may be augmented by exploring the commentary appended to these pictures, which adds a further level of detail providing insight into end-user interpretations. The approach – including its drawbacks – is demonstrated via a consequent dataset of pictures shared on Twitter in 2015, after a Syrian child was found drowned off the Turkish shore. Derivative imagery based upon the original photographs referenced longstanding iconographic themes.

Keywords
iconology, digital methods, Syrian refugee crisis, Alan Kurdi, machine learning, data analytics

1 Introduction
It has been estimated that more than 2 billion pictures are shared daily – on such platforms as Twitter, for example, more than 50% of posts contain pictures or video (Meeker, 2016, 2019). Many users on social-media platforms post pictures related to current events. When a story goes viral on a platform, there is an intense, yet circumscribed period of sharing – stories, news links, reactions, and very often pictures (Nahon & Hemsley, 2013). These pictures provide insights into the pictures that resonate with users, particularly when the subject is under such intense media coverage that there are several pictorial options to share. These pictures provide a form of framing for the subject, but they do not emerge ex nihilo. Many pictures have longstanding connections to imagery from the past that structures the viewer’s experience – and subsequent interpretation. Using Aby Warburg’s iconology as a starting-point, I propose a form of digitally-assisted iconology. It has wide applicability across multiple digital spheres, particularly archives that contain hundreds or thousands of artefacts. It is suited especially to social media posts. The form of iconology presented here is a bottom-up, reception-based approach. The method employs machine learning as a tool to cluster a large volume of images according to their formal similarities. This acts as a filtering system to help perceive thematic clusters in the presentation of subject matter. In addition, by introducing data analytics to the study, one may gain a contextualised understanding of the types of pictures that appear to resonate with social-media users.

This paper covers both theoretical and practical information for performing such research. Its utility is demonstrated by examining sharing patterns of the most-shared pictures framing the death of Alan Kurdi, a Syrian refugee, in September 2015. Photographs of
the dead child were widely shared online. Within hours, sculptors, illustrators, and political cartoonists across the world provided mediated versions derived from these photographs. This paper will demonstrate the ways in which these pictures contextualised Alan’s death in iconologically-familiar ways; it will also briefly review the textual commentaries users made as they tried to make sense of the child’s death.

2 Analysing image collections: Breadth and depth

When users post during viral events, the result can easily amount to tens of thousands of pictures. At such a large scale, and with such a likely repetition of imagery – several users often share the same picture, or slight variants of the picture – creating practical methods for researching them is a challenging priority.

To manage this flow of images from social media, researchers typically filter their subject either by taking advantage of an ad-hoc folksonomy developed through consciously-added hashtags (Vis, 2013) or through available metadata, such as geotags (Manovich, Tifentale, Yazdani, & Chow, 2014). Attendant textual content, then, forms the initial approach for collecting the corpus of imagery in the first place, and thus text and textual metadata act as proxy – and filter – for a picture’s content. The post’s text indicates that the picture is related to the subject in some fashion.1

How, then, to analyse the pictorial output shared by people of a particular event or subject? Approaches polarise along an axis of breadth and depth. The “cultural analytics” approach focuses on breadth by emphasising computational analysis, and can examine hundreds of thousands of images (Hochman & Manovich, 2013). The software (typically ImageMeasure) analyses elements such as hue and saturation for image collections, plotting the results on a graph (typically using ImagePlot). This method is limited by the software’s capabilities, as for example ImageMeasure reduces a complex array of lines and colours to a single averaged colour value. It can also be limited by metadata such as timestamp or geolocation – in short, tabulated, computationally-analysable data. Whilst at first the approach was offered as a fully-functional, computation-first method, more recently, Manovich (2020) has championed the approach to challenge research assumptions: in other words, its primary value has come to be seen as a preliminary step.

Others have used machine learning to query datasets. Impett and Süsstrunk (2016) used machine learning to examine the variation of poses on a sample of the panel boards of the Bilderatlas Mnemosyne, an early 20th-century project by the art historian Aby Warburg (2020) that employed photographic montage to compare the re-use since antiquity of visually-similar, but textually unrelated motifs (see below). They were able to note slight variations in some dozen poses, but were not able to address the use of those poses. In addition, whilst they used algorithms, Impett and Süsstrunk relied upon crowdsourced annotation of poses prior to their evaluation by the algorithm – in other words, substantial human effort.

Closer to the approach advocated below, Wevers and Smits (2018) used machine learning to filter through datasets of digitised advertisements and newspaper illustrations from the 20th century. The algorithm was focused on the visual characteristics of newspaper illustrations, and thus was able to distinguish between engravings and halftones, demonstrating the growing impact of photography over time – the contrast in visual density between the two formed the basis of the algorithm’s distinction. The algorithm

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1 That said, text is an imperfect guide. Some users will “hijack” a subject to promote their own interests, with imagery related to these different interests. The dataset examined here is not immune to that; activists in Pakistan’s Baluchistan, for example, used the terms specific to the death of Alan to publicise their own cause. Conversely, users who post pictures without using anticipated terms will escape collection. For example, imagine a picture of Alan posted alongside two words: “How tragic.” The phrase does not reference Alan, however heartfelt, and can be applied to many contexts. Collecting all posts with the phrase would result in many “false positives”, i.e., posts that have nothing to do with Alan.
was likewise able to identify the presence of chess illustrations and barometer readings reliably, both of which were presented in uniform fashions; the compositions of advertisements were also arranged in gross clusters based upon their layout, e.g., a large image at the top of the page, a block of text, and a smaller illustration isolated at the bottom. Further delineation of this content proved less reliable, as it depended upon identifying the content within the advertisements. Nevertheless, Wevers and Smits were able to demonstrate that a large, varied dataset could be clustered in ways that could prove useful for further research.

Noncomputational approaches to image datasets are also used – indeed, they are more common, perhaps the foremost being content analysis (Bell, 2004). They are labour-intensive, typically employed on a small subset of shared imagery, such as the most shared pictures or a random sample. Given the time involved and the goal of objective analysis of pictorial content, the content of pictures is categorised in as uncontroversial way as possible. This can miss out on a lot of detail, as the classification of pictorial content can be quite ambiguous. This issue is all the more acute when the dataset runs into the several thousands (Murthy, Gross, & McGarry, 2016). Still smaller-scale content analyses provide a depth of analysis whilst sacrificing breadth (Thelwall et al., 2016). At this extreme end of the breadth/depth axis, semiotic approaches focus intensely upon a single image/motif or a small handful of pictures (Bonilla & Rosa, 2015; Impara, 2018).

Art historians have often used a method that attempts to balance depth and breadth: iconology. There are several versions of iconology: It reaches back to Cesare Ripa (1593), and was originally a descriptive enterprise to aid artists to understand and depict symbolic classic personifications and their attributes. Iconology only came to become a form of analysis later, in the early 20th century. Whilst intended as a guide to fine art, even Ripa’s presentation simultaneously sourced content from perceived registers of “high” and “low” art, e.g., sculptures and coins. From the start, then, there exists an implicit assumption that e.g., attributes are communicative tools that span these cultural registers. This spanning of “high” and “low” art has continued throughout all subsequent forms of iconology and forms an important characteristic of the method.

The most familiar form of iconology is Erwin Panofsky’s (1955/1982) tripartite schema. Used in art-historical contexts, it focuses in turn upon the identification of constituent elements (pre-iconographic description), the analysis of that content (iconographic analysis), and subsequent interpretation (iconological interpretation). For Panofsky, the work of interpretation situated the work as emblematic of either its time or of the artist in question. His method is useful – and influential – because it is well articulated. However, it focuses on text-sourced imagery, for example the Biblical story of Judith and Holofernes. It tends to fail when a textual source is lacking (Kubler, 1962; Taylor, 2008) or even if sources are ambiguous or contradictory (Bann, 1998; Taylor, 1995). It also favours the iconologist’s interpretation over others, since the iconologist emphasises the relevant textual referents (Moxey, 1993). W.J.T. Mitchell (1994, p. 20) instead called for an iconology de-centred from the iconologist, calling for an approach that focused on the structuring forces of ideology such as “the observer/spectator’s body as marked by gender, class, or ethnicity”. Nevertheless, a recognisably Panofskian iconology has been used in several modernised approaches to the interpretation of imagery, in particular the identification of recurring iconographic themes, particularly in political contexts, e.g., long-standing international motifs (Fleckner, Warnke, & Ziegler, 2011), the history of refugee iconography (Warnke, 2016), American political iconography (Cavicchi, 2021), and the iconographic connection between pop culture and historical events (Kohns, 2013). Müller, Kappas, and Olk (2012) have employed the method on press photography, using psychological reaction measurements such as eye-tracking to bolster their claims.

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2 It may be a source of confusion that the method is named iconology and one of the steps is named iconological interpretation. Whilst the replication of the term is unfortunate, changing these terms would likely cause further confusion for those familiar with the method.
For the purposes of analysing digital content, Panofsky’s text-based approach is limited beyond the original collection of data – that is, beyond the original collection of imagery based upon hashtag folksonomy and other content, e.g., commentary or links. These act as the “text” and as such digital approaches to a particular subject is just as dependent upon texts as Panofsky’s iconology. Text is the necessary foundation for data gathering, but it is limited. Whilst one hopes to collect all the relevant imagery for the subject, by definition text-oriented data collection necessarily ignores any post (and accompanying image) that does not carry the terms encompassed by the initial textual search. Visually, Panofsky’s text-first approach is equally limited for the purposes of algorithmic content identification because text-based subject matter can be depicted in very different ways – to use a classic example, see any number of renditions of Judith beheading Holofernes, which look sufficiently different from one another that a computer-vision algorithm is unlikely to associate them. The scope of Panofsky’s iconology, whilst often potentially greater than the other methods referenced above, is thus truncated.

We might benefit from Aby Warburg’s form of iconology, which preceded Panofsky’s. Warburg’s approach is generally less known, in part because its practical application is not as clearly-articulated as Panofsky’s. Nevertheless, it is more expansive: Among other concerns, Warburg was particularly interested in works outside the register of “high” art, including inter alia photographs from newspapers and medieval manuscripts alongside frescoes from the great names of the Italian Renaissance. Whilst he certainly included textual sources, Warburg placed primacy upon visual stylistics such as pose, gesture, and emotional display, which he called Pathosformeln, or “emotional formulae” often sourced from antiquity (Warburg, 1907/1999, p. 249). These elements can be – and frequently were – used to depict subjects sourced from very different texts. Warburg illustrated this process over the 79 panel boards of the aforementioned Bilderatlas. One example of this phenomenon is shown on panel 42: images of figures grieving over prone dying or dead figures in subjects as ostensibly different as the death of Meleager, the burial of Christ, or the rendition of a saint’s miracles (Warburg, 2020, pp. 92–93). Whilst the subject matter (the basis of Panofsky’s iconology) differs between these different examples, visually speaking, the poses in those subjects employed a “traceable inventory of pre-coined expressions” (Warburg, 1929/2015, p. 280), based upon similar figurative position and emotional display but for different purposes. This “traceable inventory” provides a thematic way to present a narrow subject, e.g., mourning over a body, regardless of the specific subject; alternately, a pose in the inventory may show ecstasy in one venue and grief in another (Wind, 1937). A Warburgian approach has also been adopted for examining contemporary political moments, particularly those regarding the cruel exercise of power or heightened emotions – unsurprising given that Pathosformeln are indicative of aroused states (Drainville, 2018; Eisenman, 2007; Hristova, 2013).

More broadly, Warburg has been both influence and inspiration for digital research. Warnke (2011 / 2013) introduced “HyperImage”, a digital platform inspired by the Bilderatlas in which users could manually link pictures with information generated by the researcher, and Impett and Süsstrunk (2016) computationally quantified and identified the presence of Pathosformeln in the Bilderatlas. Both require human effort: The software acts as a step in the researcher’s method and does not place the software in a privileged position. Unfortunately, neither of these provide guidance for the current project. Warnke’s software has been discontinued, whilst Impett and Süsstrunk’s aim was to cluster similar poses and did not address the larger Warburgian question of the varied use of those poses.

An approach based upon Warburg’s Pathosformeln – poses used for different purposes – aligns more closely with the strengths of computer vision, particularly machine learning, which is based upon tracing statistically-similar patterns of pixel clusters (Drainville & Vis, 2022; Smits & Wevers, 2021). In the example of panel 42 of the Bilderatlas, this amounts to a broader similarity of prone figures posed besides standing figures, based upon elements of composition and contrast,
that serve an overall theme dedicated to grieving over the dead. Warburg’s pose-first approach thus presents distinct advantages to those who analyse a corpus of digitally imagery with computer vision.

3 Proposal: A digitally-assisted iconology

This paper assumes that a series of pictures has been downloaded from a digital platform, and that the downloading was predicated upon some form of textual filter such as keyword, geolocation, or timestamp. The approach outlined here articulates a version of Warburg’s method that can be rationalised and integrated with the output of computer vision algorithms. There is a certain “family resemblance” to Panofsky’s approach in that it is divided into three parts, but it differs considerably in that it focuses on pose and plays to the strengths of machine learning.

3.1 Clustering

Panofsky’s pre-iconographic analysis focused upon identifying the basic building-blocks of representational art, e.g., the presence and identification of a figure, armour, and a dragon. Algorithmically speaking this sort of analysis is dependent upon pre-existing efforts to identify, or “classify” similar content. Machine learning is fairly reliable in clustering visually-similar imagery; in contrast, their efforts of content identification are unreliable, as they are often faulty, limited, and profoundly biased (Drainville & Vis, 2022; Smits & Wevers, 2021). It is thus advisable to avoid content identification in favour of clustering visual representations along Warburgian lines.

Clustering through unsupervised neural network algorithms is the first, pre-descriptive step in a digital iconology. As an automated step, it plays to the strengths of computer vision and cleaves closely to multiple forms of formal stylistic considerations. For instance, computer vision will cluster together various framing shots familiar to photography, such as medium shots and close-ups, but will extend this to cluster similar illustrations or the presence of text on a picture. Whilst the subject matter may differ profoundly, similar depictions of, e.g., a crowd of people reflects Warburg’s interest in “pre-coined” renditions of gesture and pose, employing emotive expressions that span a variety of subject matter. As with Wevers and Smits (2018), clustering visually-similar imagery can lead to a better understanding of an archive’s contents for subsequent analysis.

There are multiple tools that take advantage of machine learning. This article will suggest two, based upon practical considerations. Their utility varies depending upon the size of the dataset, and will be illustrated below.

PicArrange is a desktop application developed by the Visual Computing lab at the Berlin Hochschule für Technik und Wirtschaft (Barthel, Hezel, Schall, & Jung, 2019). It clusters visually-similar pictures together in a reliable fashion using machine learning. Its straightforward interface is useful for smaller datasets (± 2000 pictures) where the clusters may be separated easily by the user; based upon a GUI, it is also user-friendly. PicArrange’s interface is less suitable for datasets numbering in the tens of thousands or more, however. It is easier to informally detect the divisions in a dataset of a few thousand, but that task is far more difficult as the dataset grows.

Larger datasets would benefit from more in-depth tools such as Iconographic Visualisation in Python (IVPY) by Damon Crockett (2019) or PixPlot by Douglas Duhaime (2019). Both are run locally with the results rendered in a web browser. PixPlot arranges the contents of a dataset in a floating 3D arrangement whereby visually-similar pictures are clustered together. One can zoom in and navigate through clusters of photographs. In line with much of machine-learning, it relies heavily upon a powerful GPU, and this is not available on most consumer-level computers. IVPY, on the other hand, can run on more modest hardware, and is therefore the software that will be this paper’s focus. It is also a multi-faceted tool, capable of provid-

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ing Cultural Analytics analysis as outlined above. One of its functions clusters datasets according to “neural similarity”, or visually-similar clusters using machine learning. Clusters can be divided into user-defined sizes to view larger or smaller clustering groups, which aids in the filtering of larger datasets into more manageable chunks. However, operating IVPY and PixPlot is more complex compared with PicArrange’s, as both rely upon some familiarity with programming.

The computational approach advocated here is cautious in that it plays to the strengths of machine learning – visual similarity – whilst avoiding the pitfalls – of faulty and simplistic content identification. Accordingly, studies that strive for a more automated analysis tend to narrowly define the focus of their studies (Wevers & Smits, 2018).

3.2 Thematic analysis

Computer vision clusters additional materials beyond the “pre-coined” expressive values of pose and gesture: The framing of shots, the presence of signs or banners, and other compositional elements also “nudge” the viewer’s interpretation of the depicted event.

The purpose of clustering images is to palpate an otherwise large dataset – the “great unseen” swathe of pictures that are frequently overlooked, but which may form the majority of an archive (Smits & Asser, 2022, p. 5). However, automated results are imperfect. Ostensibly dissimilar pictures sometimes appear within a clustered section, and similar pictures may be separated from one another. Automated results miss the subtleties of emotional display in favour of grosser compositional components. More importantly, the non-relational nature of computer vision provides little insight into the patterns through which pose and composition are employed: They merely demonstrate that they have been employed.

The purpose of thematic analysis, then, is to filter through these clusters and discern the ways in which events have been rendered. For example, a dataset may contain two sets of pictures: wide-angle shots of large groups of people and pictures of individuals exclusively. These may be understood as visual themes that the photographer or illustrator chose to portray – and that social media users, in turn, responded to those pictures.

3.3 Interpretative analysis

Interpretative analysis illustrates the ways elements in a picture are assembled to construct meaning for the viewer, and interpretation lies above the thematic layer. Pictorial themes shared in the context of a particular subject structure the viewer’s perception of the event. To continue our earlier example: wide-angle shots of large groups of people suggest that photographers are attempting to provide a sense of scale. In contrast, pictures of individuals suggest personalising the event in question.

The validity of these interpretations may be compared with the texts in the posts accompanying these pictures. Users may either share an article from another source, in which case the picture comes from that source; alternately, the user may pick a particular picture they find important or relevant to the discussion. In either case, users frequently comment upon the subject matter, and these can provide valuable interpretative clues regarding the user’s reception of the picture they post.

This process of examining shared imagery, examining the commentary, and tracking the referents can uncover complex, interlocking themes spanning image and text. They may provide evidence of iconographic awareness, for example, understanding the symbolic components of a picture. They likely refer to “heterodox” sources, i.e., imagery other than standard art-historical examples. These sources, e.g., popular movies, often themselves have connections to earlier image sources and thus act as links in the “traceable inventory” of “pre-coined expressions”.

Tracing these disparate components can be challenging, as patterns of textual communication may be expressed in multiple ways. Some tools, such as data analytics, can provide information on the precise time of posting and the networks of connections between different users. Detecting visual and textual patterns is manual labour that cannot be reliably automated: Communicative subtleties, including but not limited to sarcasm, are frequently missed by algorithms. Practically speaking, these patterns may be
detected and tracked through multiple tools: A database is useful but is only available for those who can make them. A more accessible solution is to track patterns of commentary and references with a spreadsheet.

The approach briefly outlined here has wide applicability. Its applicability is widest with social media due to the existence of structured data that accompanies the provision of pictures. The approach will now be demonstrated.

4 Demonstration: The death of Alan Kurdi and the refugee crisis

On 2 September 2015, the body of the two-year-old Syrian child Alan Kurdi washed up on the shore of Bodrum, Turkey. His family had fled the Syrian civil war and attempted to sail to Greece, but their boat capsized; of the family, only Alan’s father survived. Nilüfer Demır photographed his body as local police collected the child and other victims. Within hours, Demır’s photograph series had been published by her news agency’s website, DHA, and then by notable local and regional figures; it gained international prominence when Washington Post Middle East correspondent Liz Sly posted one of the photographs on Twitter (D’Orazio, 2015). Various international newspapers and individuals thereupon started sharing Demır’s photographs and the child’s death became a viral story. Over the next two weeks, Alan’s story was mixed with the story of other refugees attempting to flee to Europe; over 1.5 million posts carried pictures of Alan and other refugees alongside various terms, including “Syrian boy”, “refugees welcome”, and “kıyıya vu-ran insanlık” (Turkish for “Humanity washed ashore”). The sharing of Alan’s image had a powerful affective impact: Within a week, hundreds of thousands marched in various countries, and the default term for those fleeing the civil war changed from “migrant” to “refugee” (D’Orazio, 2015). The pictures of Alan, then, not only joined other images related to the ongoing Syrian refugee crisis, they profoundly inflected the discourse surrounding refugees, catalysed popular movements to welcome refugees across the world, albeit briefly.5

Of the 201 000 tweets containing pictures, some 67 000 remain extant. Using IVPY helps make sense of such a large array of pictures, but doing so requires some experimentation. IVPY’s clusters are not defined by the dataset’s feature set, but by a user-defined number of clusters – too few clusters and the software will generalise features to the extent that ostensibly clear distinctions between pictures are ignored; too many clusters, and the software seems to split hairs and distinguish between pictorial versions based upon, e.g., variations in cropping. Accordingly, the entire dataset was run through IVPY multiple times to arrive at the optimal number of clusters. Thirty clusters showed clear distinctions between the images. As in many viral events, many people shared the same picture, or one with slight variations. Figure 1, top, shows an IVPY cluster of a widely-shared photograph showing policeman Sgt. Çıplak carrying Alan away from the shore.6

The views presented by IVPY, then, demonstrate which pictures were shared, but this macro view provides scant context. Data analytics can fill in some data – for example, the volume of sharing for individual posts and the identity of the sharer – but joining the image to its post and its attendant analytics is currently difficult on a large scale, as this is a manual process. Filtering down to a smaller subset is a worthwhile and common practice.

One option is to examine which pictures were shared most often, which uses data analytics to discern the volume of sharing. Sharing in viral events tends to follow a power-law distribution: The majority of posts are shared by a small minority of people (Nahon & Hemsley, 2013). The data surrounding Alan Kurdi follows suit: 1640 posts provided nearly 87% of all the posts retweeted by users. Acting upon these posts – that is, by reposting

5 The impact of such pictures is measurable, but the long-term effect is limited. Viewing of affective pictures has a profound impact on empathy and in terms of real-world donations to e.g., the Red Cross – but both wane quickly (Slovic, Västfjäll, Erlandsson, & Gregory, 2017).
6 Other photographs are mixed into this cluster, demonstrating that algorithmic clustering is imperfect.
Figure 1: Comparison: IVPY (top) and PicArrange (bottom)

Note: Top: IVPY, cluster #2 of 30, Alan carried by Sgt Çiçek. Bottom: PicArrange. A sample of the pictures in the 1788 most-shared pictures, here focusing on illustrations and political cartoons.
or “retweeting” them – indicates a user's level of engagement beyond merely seeing a post in one's feed.7 These posts resonated with users in some fashion, and it is reasonable to focus on the 1788 pictures shared in these posts (some posts shared more than one picture). PicArrange can easily provide an overview of these most-shared pictures (Figure 1, bottom). Like IVPY, it too demonstrates that multiple users shared the same picture, but the smaller sample size is more comprehensible within its interface.

Thematic analysis of clustered pictures suggests commonalities among the depictions of Alan Kurdi. The child was depicted directly via Demir’s photographs 150 times (six photographs, 1 of which cropped in 2 different ways); he was shown alive from family snapshots 91 times (7 different photos, two of which cropped 2 different ways); and both of these were shown further mediated in images of newspaper covers 38 times (32 of them showing the child dead). The most common form of depicting Alan, however, was through artistic mediation: Illustrations representing him appear 291 times. Because of the distressing nature of these photographs, the rest of the analysis will focus upon the manipulation of Alan's image by various illustrators and artists.

These artistic mediations were based nearly universally upon Demir’s photographs, particularly of Alan alone (including crops of Sgt Çiplak standing over the child). By removing context around the child, illustrators evidently could append their own interpretations of the image. Using Warburg’s Bilderatlas as inspiration, and expanding it by using the concept of Venn diagrams, one can manually visualise overlapping thematic clusters in representations of the child (Figure 2).8

As with the previous figure, however, the Venn diagram presents a somewhat flat view of the imagery: There is no indication of the degree of viewer receptivity to these pictures vis-à-vis one another. Data analytics provide such contextualisation. The number of retweets – again, the number of times other users encountered a particular picture in a post, and then actively re-posted it – provides a basic understanding of the themes that resonated with users. In descending order of thematic receptivity (with significant overlaps between themes):

<table>
<thead>
<tr>
<th>Theme</th>
<th># Retweets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oversized monument</td>
<td>35,754</td>
</tr>
<tr>
<td>Commemoration / Other</td>
<td>28,538</td>
</tr>
<tr>
<td>Childhood</td>
<td>26,481</td>
</tr>
<tr>
<td>Sleep</td>
<td>22,644</td>
</tr>
<tr>
<td>Spiritual / Haunting</td>
<td>14,036</td>
</tr>
<tr>
<td>Politics</td>
<td>8,743</td>
</tr>
<tr>
<td>Hypocrisy / Indifference</td>
<td>7,453</td>
</tr>
<tr>
<td>Cruelty</td>
<td>6,307</td>
</tr>
<tr>
<td>Muslim Countries (substantial subset of Politics)</td>
<td>4,624</td>
</tr>
<tr>
<td>European Union (substantial subset of Politics)</td>
<td>3,953</td>
</tr>
</tbody>
</table>

Mette Mortensen (2017, p. 1143) refers to these derivative images – oftentimes referred to “memes” – as “appropriations” of the original photographic series, describing them as “instrumental in iconication processes. They confirm and consolidate the iconic status by recycling the image in question”. It seems, however, that instead of being instrumental in turning Alan into an icon, these derivations recognise the iconographic themes latent in the original photographic series and bring them to the surface. By isolating the child from his surrounding context, these iconographic themes were elaborated more clearly. Three themes have longstanding iconological histories: sleep and death, children as angels, and the oversized monument.

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7 Seeing a post in one’s feed is an example of an “impression”, an algorithmically-generated metric that estimates the likelihood a user will have encountered a post. This is heavily biased towards popular or well-known entities, such as the New York Times. This metric is avoided because its method of calculation is unclear, and there is an insufficient amount of data to assess the viewer’s reception of pictures encountered through one’s feed without further interaction.

8 Note that Lina Abgaradeh’s picture is duplicated, as it fits in two distantly-located sets that otherwise do not overlap – it directly depicts sleep and also directly references cruelty. This presentational limitation highlights the value of an interactive approach such as PixPlot’s.
Figure 2: Venn diagram of clustered themes

Note: Venn diagram illustrating clustered themes in the representation of Alan Kurdi. Collage by the author.
4.1 Sleep and death
Several illustrators focused on the similarity of Alan’s body pose to that of a sleeping toddler. Some, like Lina Abgaradeh, or Nahar Bahij, explicitly connect the reality of Alan’s fate with what “should” have been the case – that he should have been sleeping like any other toddler; others, like Omer Tosun, instead simply convert the image of Alan on the beach as instead lying in bed at night. This interpretation is based closely on the child’s position, which, when isolated from his surroundings, can remind the viewer of sleep.

There is a deep, multicultural history of iconological connections between sleep and death, particularly in literary imagery, and these connections span multiple cultures – underscored by the fact that the vast majority of the artists using this theme come from the Middle East, Turkey, and India. The Greek gods of death (Thanatos) and sleep (Hypnos) are portrayed as brothers, as are their Roman counterparts, Mors and Somnus (Panofsky, 1964, Figs. 102, 105, 115, 123). The Old and New Testaments repeat the image, e.g., “Enlighten my eyes that I never sleep in death” (Psalm 12:4) and “Lazarus our friend sleepeth, but I go that I may awake him out of sleep” (John 11:11). In North African Sufi traditions, the deceased holy man (marabout) is not considered dead, but sleeping in his tomb (Turner, 1974 / 1998, p. 68). In Hamlet, Shakespeare refers to the “sleep of death”; and even today, we might use the term RIP (short for Requiescat in pace, or rest in peace) to refer to death, even symbolically, e.g., “RIP my bank account”. This underlying theme adds poignancy to broader representations referring to sleep such as blankets or other elements of childhood, such as naps, toys, and child pastimes (Figure 3).

4.2 The child as angel
The spiritual / haunting theme (Figure 4, left) focuses upon supernatural elements. Ahmed Kaoud, “Zezo” (Zezo Al Yazidi), and “Ygreck” (Yannick Lemay) depict the child as held aloft by supernatural forces: Zezo’s watery hand

Figure 3: Two themes: Sleep and Childhood

Note: Two major themes: Sleep as a major thematic focus, and childhood themes inserted into the representation of Alan. Collage by the author.
removes the child from bloody conflict to deposit him onto the shores of Jannah (paradise). The widely-shared picture by Khalid Albaih depicts Alan twice, once held in the arms of an angel and again lying on the beach.

The depiction of Alan as an angel is prominent in these supernatural depictions. Two images – the widely-shared picture by Islam Gawish and the aforementioned Kaoud – are based upon Demir’s imagery. Nasser Jafari and Ferran Martin wholly reimagine the child separate from Demir’s photos.

The term “angel” is a common metaphor for childhood innocence and sweetness, and its visual cognate has been employed since the Renaissance as putti. One of the most familiar examples is the two angels depicted in the Dresden Madonna by Raphael (Figure 4, right) and the subsequent reception of this panel has an impact to the present day. This painting was deemed a masterpiece by the nineteenth century, a point where the imaginary surrounding childhood focused upon sentiment and which coalesced into political campaigns against child labour (Ariès, 1962; Belting, 2001, pp. 50–61; Cunningham, 1995/2005, pp. 58–80). Indeed, Raphael’s putti remain sentimental favourites today, featuring on greeting cards, posters, wrapping paper, and notebooks. Several of the illustrators depicting Alan inflect the viewer’s interpretation by invoking this popular iconography.

Others emphasise a haunting, ghostly presence. Most directly, “Inkquisitive” shows the ghost of Alan looking over his body, and an anonymous illustrator depicts Alan lying in the arms of ghostly parents superimposed on the beach. Other pictures are haunted by Alan without directly showing him – the UNHCR depicted the beach upon which he was found, but replaced the body with a handheld caption stating “Sleep tight, little boy”. Mahnaz Yazdani depicted a group of children “sleeping” on the beach, with the water acting as a blanket. Yazdani’s picture is unthinkable without Demir’s photographs of Alan; those who posted the picture explicitly refer-
ence Alan or the hashtag “humanity washed ashore” used to reference him.

4.3 The oversized monument
Seven artists – two sand sculptors, one graffiti artist, and the rest using illustration as their medium – depicted Alan larger than life (Figure 5, top). These renditions constitute the most widely-shared theme, due to the single most widely-shared derivative image – Asit Kumar’s photograph showing Sudarsan Pattnaik at work on his beach sculpture.

Most of the renditions of Alan as oversized are inflected by opprobrium. Wissam al Jazairy places blame for his death through neglect by placing him in the centre of the UN’s Security Council; “MSamir” places the child in the centre of an Arab League meeting.
ing mistaken for the Security Council in the dataset). The two enlarge Alan to emphasise the willful blindness of politicians; despite his size, politicians still carry on their business as normal. Rafat Alkhateeb portrays a “New World Map”, in which a giant Alan’s arrival to the shore is barred by barbed wire. Le Monde’s “Kichika”, in turn, voices outrage at the media spectacle as the giant Alan is surrounded by photographers. Sudarsan Pattnaik and Osama Esbaiteh provide additional resonance with their chosen medium – sand on a beach, near the water’s edge – thus linking their work with the context of Alan’s death.

Commemorating a death – particularly a notable death – by rendering the body at a larger-than-life scale is common in funereal sculpture. As above, the body is usually rendered to partake of the broader iconographic theme of sleep and death. Violet Manners’ sculpture of her deceased son represents these characteristics (Figure 5, bottom). The child, who died at nine years old, is presented at an adult’s scale; having been rendered in a shroud on a pillow, Manners has employed standard characteristics of sarcophagi for hundreds, if not thousands, of years (Panofsky, 1964).

It is not clear whether the artists and illustrators here intended to portray Alan as a funeral sculpture. However, the rendition of a corpse, particularly oversized, is unthinkable without the history of tomb monuments. Comments arising from users posting these monumental pictures, however, employ terms that suggest the format nudged their interpretations to view them as ad hoc funerary monuments. We will now turn to these comments for further illumination of user interpretation.

### 4.4 User interpretations

Soon after the initial photographs of Alan appeared online, many in the wider world remarked upon the similarity of Alan’s pose to that of a sleeping child, including Prime Minister Harper of Canada (whose government denied asylum to Alan’s family), Liz Sly, the Washington Post journalist who was instrumental for introducing the story to the world’s press, and Uğur Çebeci, the editor of the Turkish newspaper that initially published the photos of Alan (Peat, 2015; Pekel & van de Reijt, 2016, 3:30; Sly, 2015). Twitter users also reference the equation of death and sleep, albeit obliquely. They refer to sleep (“He’s asleep, but we’re the ones who have to wake up”). They frequently comment “Good night, Alan”, and even more frequently comment “RIP”. Only one user explicitly conflates sleep and death: The image is unbearable because it “reflects a living, sleeping child”. These oblique references may be due to Twitter’s affordances. As a medium which places a considerable premium upon the written word (at the time, tweets could only be 240 characters in length), many users seem to let the pictures “speak for themselves”, at least through a seemingly legible iconographic theme as a source of affect in their commentaries.

Monumentality is also obliquely referenced in the dataset in two ways: first by commenting “RIP” / “Rest in Peace”, a phrase often placed on tombstones, intoned in funerals, and again underscoring the connection between sleep and death. Moreover, many users sharing the monumental variations by Al Jazairy, MSamir, and Alkhateeb use the phrase “Do you see it now?”, often addressed to world leaders, particularly leaders of the EU. They suggest that magnifying the child makes the refugee crisis visible to politicians. In such comments, the “it” of the phrase suggests that Alan has become symbolic of all refugees attempting to flee intolerable conditions. Indeed, in his beach sculpture, Sudarsan Pattnaik used the phrase “Humanity Washed Ashore”, also touching upon metonymy, and the phrase, a central term used when referencing the event, itself poses Alan as a metonymic monument.

Instead of only repeating the iconographic themes present in the pictures they shared, Twitter users expressed personal affective responses by using terms associated with heartbreak and mourning. Users also used imagery of Alan – especially Alkhateeb’s illustration – whilst emphasising themes of common humanity with refugees – clearly objecting to the fact that Alan and other refugees have died attempting to cross borders,

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9 To protect users’ privacy, texts will not be fully quoted, as doing so would render the poster identifiable.
which serve to divide human populations into separate groups.

Many used pictures of Alan as evidence, especially to indict politicians for their neglect. These were common sentiments with pictures that contained references to the European Union, then-prime minister of the UK David Cameron, and other figures. However, many pictures were employed to indict politicians for their inaction without reference to their specific content.

5 Problems and pitfalls

The approach outlined above suffers from the same issues encountered by anyone using software – particularly experimental software. Software has an inherent “presentist” bias, as it can only be guaranteed to work as anticipated at its time of production. Initial installation and subsequent operation of tools like IVPY or PixPlot is complex. Changes in the technology that supports the software, be it hardware, a programming language, or any of the numerous dependencies that provide various “plug-in” features, can and do render software periodically unstable or unusable, an experience familiar to many developers who rely upon open-source software. Overcoming them requires experience, elaborate workarounds, and patience. Between the creation of this article’s first and second drafts, for example, updates to one underlying dependency (Tensorflow) rendered IVPY unable to perform its “neural extraction” feature-set. The fear with using any software is that instead of being periodically unusable, it becomes “abandonware”. In those cases, replicating others’ methods can eventually become impossible. Conversely, if a tool becomes popular, it will undergo significant development, which means the tool’s output changes dramatically over time – and the ability to replicate another’s methods recedes as time passes.

The presentist bias also impacts the ability for export and/or future retrieval. Software like PicArrange, IVPY, or Yale’s PixPlot are intended for interaction, which at best assumes today’s forms of computational interaction will continue indefinitely. They frequently do not offer access to the longer lifespan of comparatively stable standards. For example, neither PicArrange nor PixPlot can export a JPEG of their visual output, as in Figure 1 – one must make do with screenshots, which by their nature are low resolution. IVPY can render a higher-resolution output, but only through a massaging of its parameters.

Finally, machine learning applications themselves suffer acutely from this presentist bias in the classification stage: Having been trained to identify a small collection of concepts, they frequently misidentify pictorial content. This problem has an oversized impact on digitised datasets. The investigation by Wevers and Smits (2018) upon historical digital archives highlights machine learning’s focus upon present-day visuality. The algorithm will struggle to recognise older forms of consumer products, for example, as it is exclusively trained on contemporary products, due in part to the ready availability of contemporary examples for training purposes in imagery sourced from the web.

In sum, there are several pitfalls with a software-centred approach – incompatibilities, abandonware, evolution, restricted output, and inadequate features. Indeed, the unstable nature of available toolsets is an underlying motivation of a digitally-assisted iconology, as it is dependent upon a process rather than any specific tool. In addition, an awareness of the limitations of classification informs the motivation for focusing upon visual similarity instead. As the tools evolve and become more mainstream, it is hoped that their usability and reliability will increase as well.

6 Conclusion

This overview presents a brief survey of a new, algorithmically-assisted approach to iconology designed for the study of imagery shared on social media. It is to be stressed that the digital tools of this approach do not in themselves take the place of the researcher. Instead, machine-learning tools such as PicArrange or IVPY cluster pictures together visually as a valuable step in the analytical process. Machine learning cannot adequately discern the content present in this or any other dataset, since the algorithmic identifi-
cation of pictorial content is faulty: That step requires substantial human analysis. That said, machine learning can undoubtedly accelerate analysis, particularly as approaches inspired by Aby Warburg – focusing on pose, and visually clustering thematic renditions – play to the strengths of machine learning.

A digitally-assisted iconology benefits from structured data, in which users, dates, and connections between users is tracked and maintained by the collecting entity, in this case Twitter. The method as described here was developed to take advantage of the data provided by Twitter, but a modified form can work with historical imagery containing metadata as well. Nevertheless, sensitive, human-oriented contextualisation and analysis is required for this work. In this instance, for a subject so harrowing – the death of a refugee during the Syrian refugee crisis – we can discern layers of interpretation, by artists and illustrators, and ultimately by the users themselves, many of which reference longstanding iconographic themes equating sleep and death, the child as an angel, and the oversized monumentality of the notable dead.

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Conflict of interests

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