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More than Distant Viewing: Qualitative Views on Machine Learning as an Automated Analysis Method in Networked Climate Image Communication

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Abstract

Machine learning algorithms are increasingly used within the digital humanities as heuristic methods in image analysis. Automated image recognition methods and the sorting of image similarities provide access to large image inventories, which are made accessible to a human eye primarily via visual distance methods. In this context, the visualisations as an interactive interface represent only one 'end product' of a dense series of both qualitative and quantitative methodological decisions within a research design. Especially these decision-making processes are the crucial points within DH research, since with them the boundaries of qualitative-image-scientific and quantitative-algorithmic approaches become perceptible. This article addresses the process of a semi-automated analysis procedure of large image data sets using Google Images on climate change as an example. It results from a case study on cross-cultural climate image comparison by the mixed-methods research team *anci*.[1] With the help of t-SNE as a machine learning method for dimensionality reduction and the k-means clustering method, the methodological process from data visualisation to visualization is made critically and reflectively transparent. The term pipeline serves as a metaphor for the methodological process.

Introduction

Algorithmic image sorting and its visualisation are increasingly used as tools in digital art history and image science. These include, among others, their use as hermeneutic and epistemic engines in art historical image search [Bell and Ommer 2018], in the organisation of museum or collection-specific image datasets [Google Arts & Culture 2011], or in digital cultural analysis [Manovich 2020]. For this reason, for example, machine learning algorithms can be used to automatically develop dimensions of image similarities. In particular, human-computer interactions are enabled in the mode of “distant viewing” [Moretti 2020]. The visualisation of abstract data allows the identification of trends and correlations in the data. A main component of distance representation lies in the rapid recognition of optical patterns on the part of the recipient [Dörk and Glinka 2018] [Dörk et al. 2020]. Graphical and image-specific methods of data representation are thus given increased attention in DH research for knowledge production and organisation – as opposed to primarily used textual methods. In our article we discuss the development of methods for a semi-automated comparison [Schnapp 2012]. 1

The starting point for these questions is our research project on intercultural comparison of climate images on the World Wide Web. Using the Internet search engine Google Images, we collected images from different regional cultural areas based on specific keywords related to climate change. Using machine learning as a digital method, we want to find out how globalised or differentiated the visual language of climate change is. For this purpose, we use a method of dimensionality reduction (t-SNE) based on machine learning algorithms, which enables human interaction with huge amounts of images by making them accessible to the human eye in the form of a data visualisation. Within our mixed-methods approach of quantitative computer science and qualitative image science, qualitative image analysis and reflection thus begins with data visualisation, which thus takes on a central role. However, our focus is not only on 2 visualisation as a quantitative end product or phenomenon. Rather, we focus on the process of data processing and its curation, to which diverse data-shaping decision-making processes are subjective: from collecting, to clustering, to visualisation. Following Johanna Drucker's statement – “distant reading isn't” [Drucker 2017, 634] – we would like to emphasise that computer-assisted image analysis including data visualisation is not only a distant viewing method in the supposed sense of viewing:

Machine learning as a method is promisingly applicable within the digital humanities, as it promises the analysis or comparison of large amounts of data. However, the automated processes only ever consider the isolated structural levels of the images. They are subject to unseen steps (black box) and qualitative-curatorial decisions. The visualisation of the data as visualisations of the distance within an operable interface is only a part of it. Although the qualitative interpretation of the automated image sorting starts from this distance view, we understand distanced seeing as the critical dialogue between the pure image artifacts and the abstracted data visualisations of computer vision [Offert and Bell 2021]. With being distanced we focus on the presupposition and technical standards that are used to abstract image data. 3

In the following, we would like to use the metaphor of the pipeline to critically explain the development process of the t-SNE method. In individual steps, we describe the process of method development and reflect on the central qualitative as well as quantitative influences. Rather than focusing on the added value of machine learning as a new method, we want to reveal how much the structure of data and information is subject to constant decision-making processes and how interdisciplinary difficulties emerge in the process. In this deliberately open and critical handling of (visualised) image data, we see the central added value of mixed-methods or DH research. 4

Methods pipeline

Within Google's image policy, one encounters a very standardised visual language, which at the same time reveals considerable differences in the preferred image types (e.g. photos, maps, curves, documents, comics) and in the framing of climate change. Our present study on the cross-cultural comparison of climate images is based on the framing approach from a qualitative image science perspective [Rodriguez and Dimitrova 2013], which was tested by means of automated image analysis. We focus on the development of a technically constructed gaze, which we critically explore in our study as part of the pipeline. Its importance is particularly evident in corpus creation and Google's page rank algorithms, as well as in image analysis based on the definition of the machine learning algorithm. This led to our central research questions: What is the role of automated image searches in terms of pre-sorting and ranking climate images? What do machine learning algorithms [Van der Maaten 2008] accomplish as a digital method for analysing image collections? To what extent are qualitative human image sorting and t-SNE visualisation interdependent? 5

As noted in the introduction, by distanced vision we mean the constant dialogue of quantitative and qualitative decision-making processes. This already becomes clear in the methodological orientation of our research project. As an interdisciplinary mixed-methods research team, we oriented ourselves to the so-called embedded design of mixed-methods research according to John W. Creswell (2007). Here, the quantitative and qualitative approaches are considered separately, but in a consciously conceived interdependence in dialogue. The focus is on the quantitative image data and their machine image comparison using t-SNE as algorithmic image sorting and visualisation and the subsequent qualitative reading of the resulting data images. 6

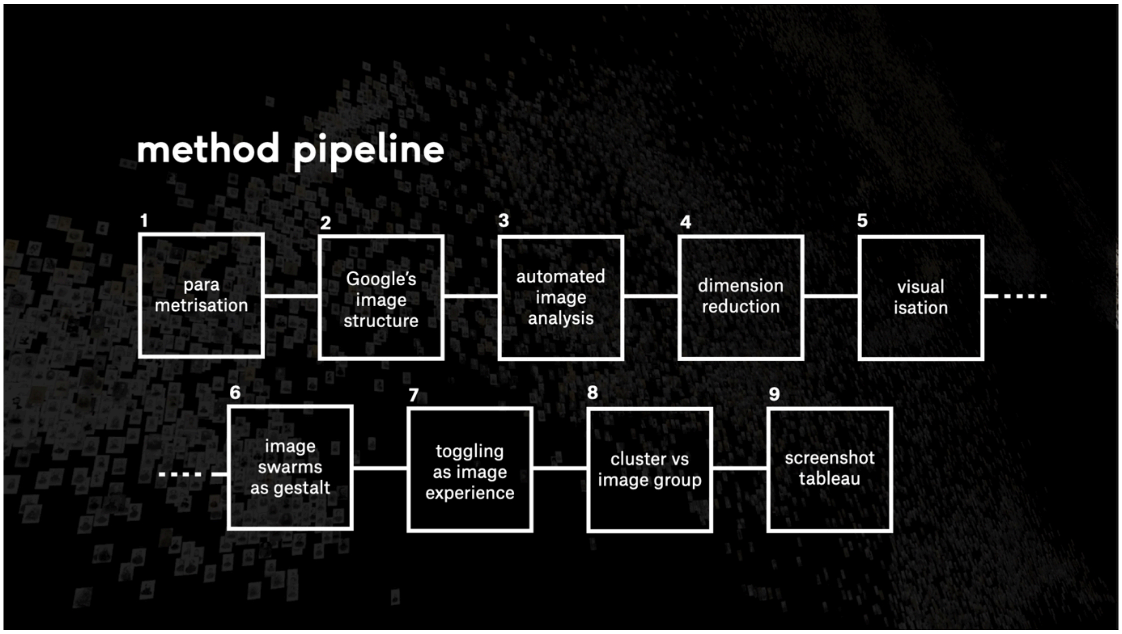


Figure 1. Diagram of the method pipeline and structure of the following keypoints

1 – Parametrisation - Thinking technically about cultural spaces

In this first step of project design, primarily qualitative distinctions are drawn and decisions are made as to which phenomena of the object of study are analytically and statistically usable. We call this basic step of formalising the research project *parameterisation*. 7

Specifically, to describe intercultural climate image communication, two basic aspects had to be formalised for our study: on the one hand, cultural spaces *per se*, and on the other hand, the spaces in which climate images circulate. Thinking technically about cultural spaces turned out to be a challenge. Our study looks at the most global arrangement of climate communication possible, made possible by infrastructures such as the internet. The political order of nation states is too reductionist in this structure, as neither networked nor intercultural spaces can be thought of with the rigid state model. The question, then, was how cultural spaces can be conceived on the Net. After discussions with cultural scholars, we decided on the concept of *locales* as a unit of cultural space. A *locale* combines the idea of a specific language with a region or country. 8

The second question about the representability of climate images related primarily to their technical media spaces, since the global reality of image communication on climate change is impossible to represent in its entirety. However, the global technology of the internet allows us to consider the cultural implications of this interconnectedness as a simplified model for cross-cultural climate communications. Compared to social media such as Instagram or Tik Tok, we were interested in the largest possible, extensively used, and highly formalized media spaces. The focus therefore fell on the search platform Google and Google Images as the largest manifestation. 9

So, in order to do justice to the technical idea of cultural spaces in the WWW and Google as a search engine, we used the notion of *locales*. We are aware that a *locale* does not correspond to the idea of a cultural space, but is a heuristic for our research questions. 10

Setting the locales

The next step was to clarify which *locales* should be compared with each other. We developed a focus list of eighteen *locales*. These *locales* form a purely subjective selection based on previous research, contacts with international researchers, and climate policy relevance. To counteract a perceived biased perspective, we supplemented this with a number-based analysis of climate indices, so that qualitative and quantitative approaches were mixed. To do this, we 11 created a two-dimensional mapping of the rankings for nation states of two climate indices: the ND-GAIN index from the Notre Dame Global Adaptation Initiative and the TCI indicator from the Stockholm Environment Institute. In a subsequent identification of groupings, we captured five clusters that outline focal points in each country's climate policy. The following seven countries were exemplary selected: USA, Brazil, Germany, Kenya, United Arab Emirates, Bangladesh, and Australia. Their *locales* were generated using simulated VPN searches.

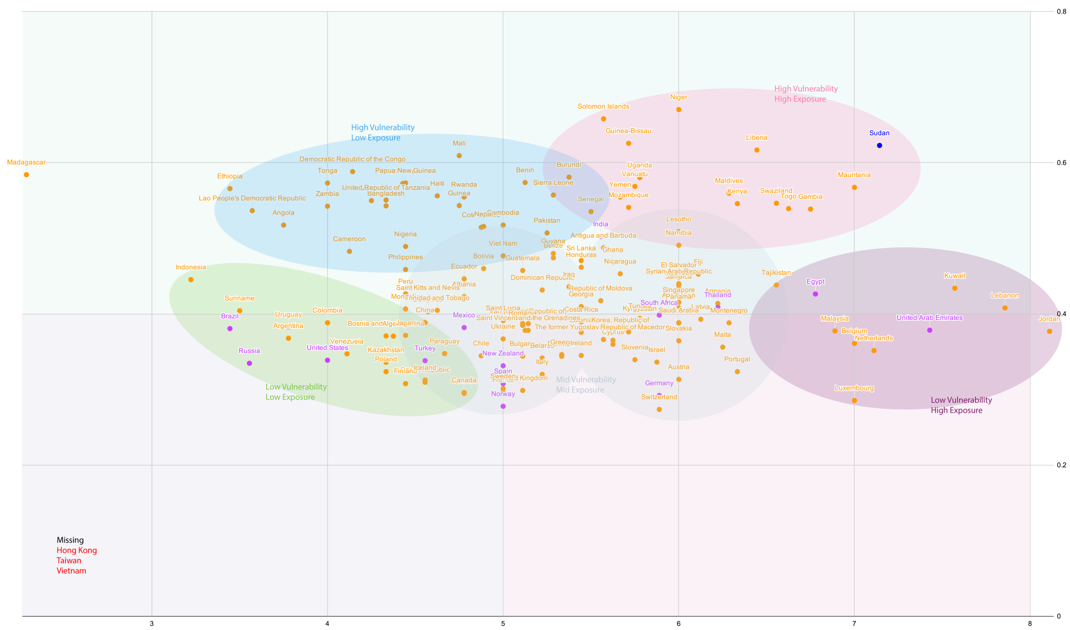
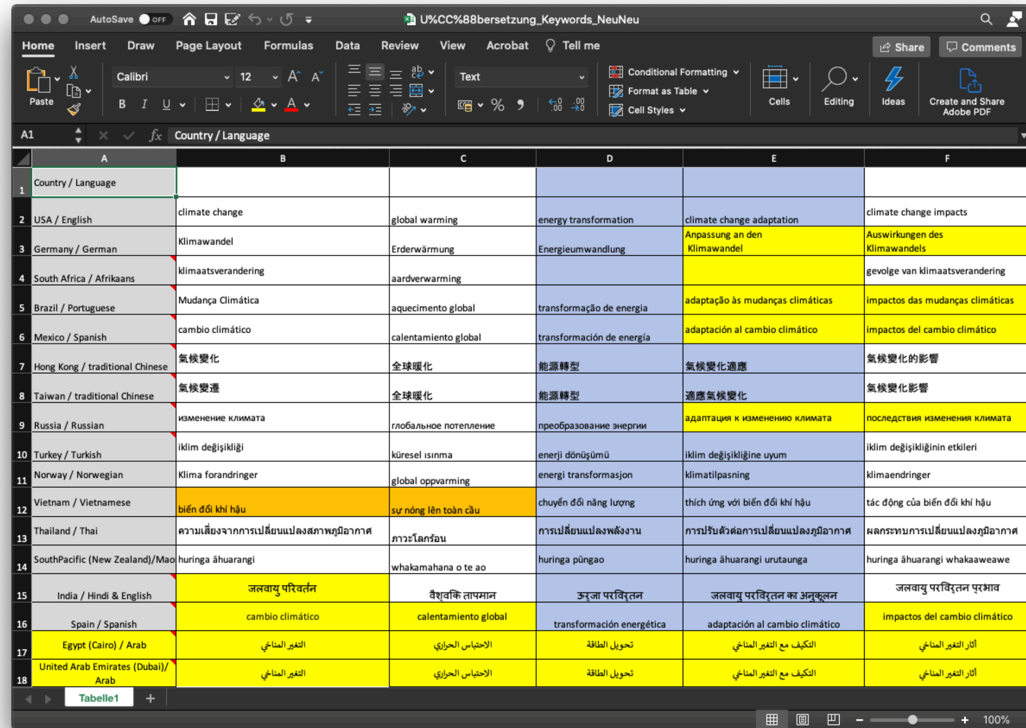


Figure 2. Mapping TCI and ND-GAIN with five resulting clusters

Google image search – keywords

Our conducted image search via Google works by keywords. We were therefore confronted with the problem of differentiating the climate change discourse into a few but essential terms. In a highly iterative and qualitative process, we randomly evaluated different keywords in different languages related to climate change discourse in Google Image Search. We coordinated the exact definition of the keywords with experts working in the field of climate research and communication. In the end, we decided on eight terms to use as keywords and search terms: (1) climate change, (2) climate change disaster, (3) climate change impacts, (4) climate change risk, (5) climate emergency, (6) climate crisis, (7) climate collapse, and (8) global warming.



	A	B	C	D	E	F
1	Country / Language					
2	USA / English	climate change	global warming	energy transformation	climate change adaptation	climate change impacts
3	Germany / German	Klimawandel	Erderwärmung	Energieumwandlung	Anpassung an den Klimawandel	Auswirkungen des Klimawandels
4	South Africa / Afrikaans	klimaatsverandering	aardverwarming			gevolge van klimaatsverandering
5	Brazil / Portuguese	Mudança Climática	aquecimento global	transformação de energia	adaptação às mudanças climáticas	impactos das mudanças climáticas
6	Mexico / Spanish	cambio climático	calentamiento global	transformación de energía	adaptación al cambio climático	impactos del cambio climático
7	Hong Kong / traditional Chinese	氣候變化	全球暖化	能源轉型	氣候變化適應	氣候變化的影響
8	Taiwan / traditional Chinese	氣候變遷	全球暖化	能源轉型	適應氣候變化	氣候變化影響
9	Russia / Russian	изменение климата	глобальное потепление	преобразование энергии	адаптация к изменению климата	последствия изменения климата
10	Turkey / Turkish	iklim değişikliği	küresel ısınma	enerji dönüşümü	iklim değişikliğine uyum	iklim değişikliğinin etkileri
11	Norway / Norwegian	Klima forandringer	global oppvarming	energi transformasjon	klimatilpasning	klimaendringer
12	Vietnam / Vietnamese	biến đổi khí hậu	sự nóng lên toàn cầu	chuyển đổi năng lượng	thích ứng với biến đổi khí hậu	tác động của biến đổi khí hậu
13	Thailand / Thai	ความเสี่ยงจากการเปลี่ยนแปลงสภาพภูมิอากาศ	ภาวะโลกร้อน	การเปลี่ยนแปลงพลังงาน	การปรับตัวต่อการเปลี่ยนแปลงภูมิอากาศ	ผลกระทบการเปลี่ยนแปลงภูมิอากาศ
14	SouthPacific (New Zealand)/Mao	huringa āhuarangi	whakamahana o te ao	huringa pūngao	huringa āhuarangi urutaunga	huringa āhuarangi whakaaweawe
15	India / Hindi & English	जलवायु परिवर्तन	वैश्विक तापमान	ऊर्जा परिवर्तन	जलवायु परिवर्तन का अनुकूलन	जलवायु परिवर्तन प्रभाव
16	Spain / Spanish	cambio climático	calentamiento global	transformación energética	adaptación al cambio climático	impactos del cambio climático
17	Egypt (Cairo) / Arab	التغير المناخي	الاحتباس الحراري	تحويل الطاقة	التكيف مع التغير المناخي	أثار التغير المناخي
18	United Arab Emirates (Dubai)/ Arab	التغير المناخي	الاحتباس الحراري	تحويل الطاقة	التكيف مع التغير المناخي	أثار التغير المناخي

Figure 3. Extract from the translation chart with confirmed keywords

2 – Google's image structure as a corpus

To create the image corpus, we extracted the essential data using the method of web scraping via a Python script (via Beautiful Soup package). Web scraping describes an automated procedure that makes it possible to retrieve specific web pages and to retrieve previously defined elements of these pages. The data was thus filtered by algorithms from the information architecture of Google Images. This procedure is equivalent to an automated, qualitative curation of images since it has to be manually decided which items from a website are taken. On the basis of the Tor browser and its VPN tunnelling capabilities we technically imitated search queries from different cultural regions concerning climate issues. 13

For seven *locales*, we agreed on a subjectively determined quantity of 250 images per keyword, since too many images would have limited the qualitative evaluation of the image analysis at the level of perception. As a tendency, it can be said that each technical arrangement benefits from more data, but must remain manageable for the human eye to ensure qualitative intervention. In addition to the image artifacts themselves, meta data of the images and the source of origin were also collected. 14

The challenge that arose in our work with Google, understood by us as an epistemic search engine, is which perspective of research with or about Google results from this. According to the media scientist Richard Rogers, two approaches can be described as “medium research” and “social research” [Rogers 2017]. Medium research asks about algorithmic mechanisms and political motivations, i.e., how a web application is designed and for whom. As a critical research strand, the technical limitations and ethical-social implications of Google and its non-public page ranking algorithms are discussed here in detail. In contrast to medium research, we have decided in favour of the second strand, social research according to Rogers. This seeks not so much to expose the secret structures of search algorithms, but rather to productively read the given structures of the algorithm. For example, Google's rankings can be understood as indicators of social trends, and questions about the popularity of search words and regional emphases can be examined. Following this principle, we made a conscious decision to use the t-SNE technology to visualise 15

Google's ordering structures that express the current social interest of global climate communication - i.e., our research subject.

3 – Automated image analysis and its opacity

Our web scraping process resulted in a corpus of approximately 16,000 images. To analyse this dataset, we searched for algorithms capable of formulating, at best, their own criteria of similarity according to which image motif recognition could be automated. 16

We used the artificial neural network method, specifically the Convolutional Neural Networks (CNN) architecture [LeChun 1999]. Another big resource factor in neural network learning is the amount of data sets required. Our 16,000 images from Google Image Search are too few to make them usable for a CNN. Again, for resource reasons, we therefore decided to use a pre-trained CNN following Google's Inception v3 architecture [Szegedy et al. 2015] based on ImageNet's image dataset [Stanford Vision Lab 2020]. In the practical application, we had the approximately 16,000 images from Google Image Search pre-processed by a Python script (via TensorFlow library) and obtained multi-dimensional similarity vectors (2048 dimensions) for each image in relation to the learned images and keywords from ImageNet by the pre-trained neural network *Inception*. 17

The identification of image similarities is central to our intercultural image comparison. It is based in the method of image comparison, which is thought of in a technical way compared to an art-historical orientation. Regarding the exploration of the quantitative technical view, similarity means the structural relation based on the trained ImageNet dataset. This can be structured in colour, shape, but also semantic content. Only differences can be made that are already created in the taxonomy of ImageNet. Since ImageNet is not specifically designed for climate change imagery and Inception has not been explicitly trained for this application, inaccuracies are to be expected. Thus, all images are compared to the broadest classification system embedded within *ImageNet* rather than particular climate image settings. In addition, due to the structural complexity of neural networks, it is difficult to identify the basis on which the algorithm has made decisions [Distill Pub 2007]. In addition to the black box in Google Images, another major discordance is evident in the work with automated image analysis using pre-trained neural networks. 18

4 – Dimension reduction or to be spoilt for choice

The 2048 dimensions of structural similarity resulting from the neural networks are difficult to imagine for the human eye, which is why we applied techniques for dimension reduction to an imaginable level in the next step. As statistical methods, such methods have been developed in many different forms and focuses. Established algorithms are, for example, principal component analysis (PCA) or newer approaches, such as UMAP (Uniform Manifold Approximation and Projection). Due to its effectiveness, performance, and resource-efficient implementation, we decided to use a t-SNE (T-distributed Stochastic Neighbour Embedding) algorithm [Van der Maaten 2008]. t-SNE is a machine learning algorithm that models high-dimensional objects through a two- or three-dimensional space in such a way that, in principle, structurally similar objects are modelled by nearby points and dissimilar objects by more distant points. These models can then be represented by plots on a surface. 19

While t-SNE plots often appear to represent groupings, these visual clusters can be strongly influenced by the calibration chosen, so a good understanding of the variables for t-SNE is necessary. Thus, the creation of a t-SNE algorithm is primarily a qualitative decision by the programmer about the variable values. Calibrating the variables is a particularly consequential step within our pipeline because it is on the basis of their data that the subsequent visualisation is created: Reducing the high-dimensional relations to a two- to three-dimensional space by the t-SNE algorithm creates distortions in the data representation in every case. They manifest themselves in the fact that very similar artefacts in a low-dimensional visualisation do not necessarily have to be in spatial proximity to each other. 20

For our analysis, we created a t-SNE calculation for each *locale* and for each keyword. We calibrated the variables the same for each *locale* due to the number of calculations and for comparability reasons. In case of doubt, however, not every t-SNE is thus optimally set up for the specific dataset. It is possible, in addition to the general bias due to dimensionality reduction, that apparent groupings are not present in the actual clustered data and thus may be spurious 21 findings. This is a principal challenge when working with automated dimension reduction and subsequent visualisation. t-SNE visualisations cannot be simply read, but should be understood primarily as a dynamic image under the calibration dependencies described.

5 – Visualisation - Qualitative reading needs visibility

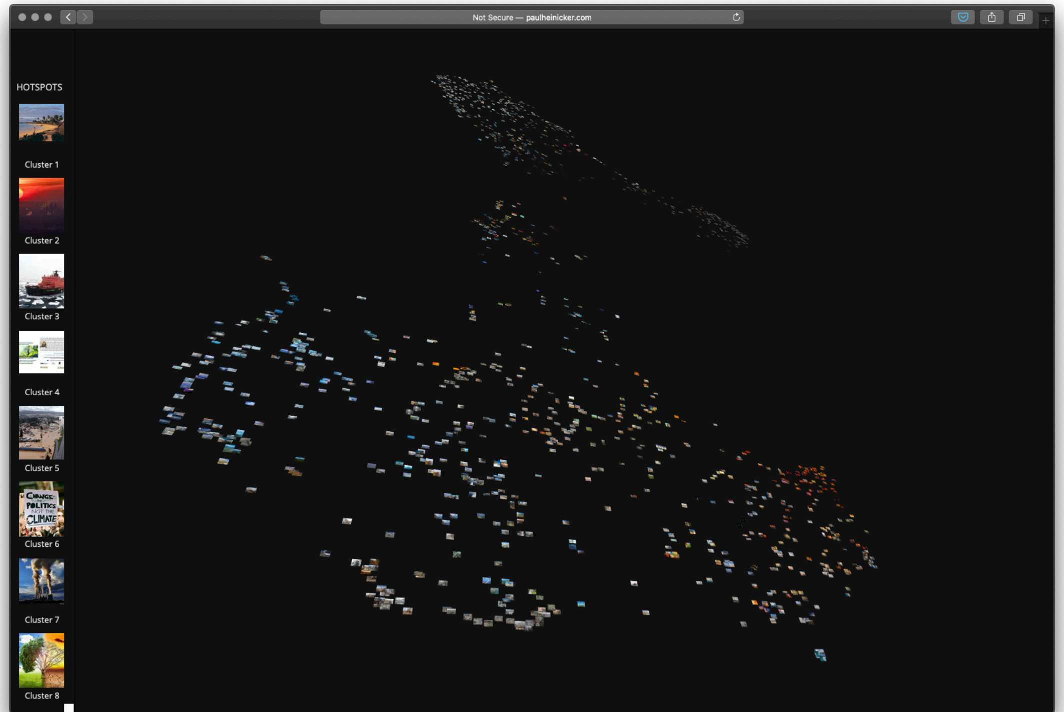


Figure 4. Screenshot of the visualisation interface based on the Yale DH framework

To merge the computational methods and the visualisation of the statistical results, we created a web interface based on Yale University's PixPlot tools with an interactive layout arrangement of the image corpus [Yale Digital Humanities Lab 2017]. The web-assisted visualisation (WebGL) consists of a two-dimensional projection in which similar images are grouped based on the similarity vectors computed by the Inception v3 neural network. 22

In a further step, we complemented a k-means clustering in the t-SNE reduced two-dimensional space of the images. Clustering is applied for the purpose of identifying major centres of the t-SNE array by numerically comparing the dimension-reduced similarity vectors. In the image analysis, these centres were referred to as *hotspots*. It should be noted, however, that t-SNE operates in continuous space, i.e., it does not group in a strict sense. Thus, not every image in t-SNE corresponds to a complete and unique centre, and thus there are no unique membership boundaries. The k-means clustering does not perform the clear identification of clusters within the t-SNE array, since the t-SNE data is not structurally meant to be clustered by proximity. From a quantitative perspective, it serves only as an additional statistical procedure to present the results for human perception in such a way that one can orient oneself in the following t-SNE visualisation. 23

At this point, the important dual role of interfaces becomes clear: On the one hand, only the visual representation allows access to the digital data structures, which are thus imperceptible to human viewers. On the other hand, the final representation allows little or no insight into the many decision-making processes, constraints, and (subjective) interventions that led to this representation. 24

From a humanities perspective, in the further course of the pipeline we asked ourselves whether and to what extent the algorithmic t-SNE procedure can be understood as a framing method for image masses. Because from the technical 25 sorting of Google's climate images, groupings of similarities resulted in this pipeline that allowed thematic image focusses.

Overall, despite *locale*-specific differences, we were able to identify the following dominant or concise main motifs and 26
image genres in the collected images, which expressed themselves either as technically generated image clusters or qualitative image groups. They can be understood as the result of climate image communication in relation to Google's ranking and image structures. In terms of image science, so-called “catch images” [Diers 1997] could be identified within the identified image groups, which were characterised by recurring motifs and formal stylistics. These appeared more frequently in the Google query due to their similarity and are reflected, among other things, in the technically generated *hotspot* images. The following overview shows the most dominant image groups with central catch images as single images.

Figure 5. Overview of all image clusters with an according catch image

In total, three image types as an average of five concise main motif groups could be located according to size: 27

1. photographs, divisible into a) a group of images on the subject of environment, nature, landscape, b) a group of people (conferences, groups, politics versus protest/demonstrations), c) a group of images with representations of the earth, and d) a group of images on the polar bear.
2. text-image documents, including text-only documents, documents with diagrams, covers of books and brochures, individual slides with text, activist posters with slogans, occasional maps, cartoons or cartoon-style graphics, infographics, and charts
3. highly artificial photomontages (representations of contrast)

Figure 6. The three different main image types or genres exemplified by the t-SNE visualisation of the German Google search query Left: Photographs, centre: text-image documents, right: artificial photo montages

It could be determined that the t-SNE algorithm thus does not sort the images exclusively according to image types and juxtaposes the image-text documents with the photographs as central image clusters, but according to similar motifs or image contents. In the t-SNE visualisations, images motivated by content – as far as one can speak of content in computer image recognition – are placed next to image clusters of another image type. This observation is significant because it shows how similar technical-automated image vision and cultural-scientific vision are on this level. 28

6 - Digital image swarms as a Gestalt

The qualitative assessment of the algorithmically sorted image motifs within the t-SNE interface was based on the reception of large image swarms in which the individual images were not perceived as such. 29

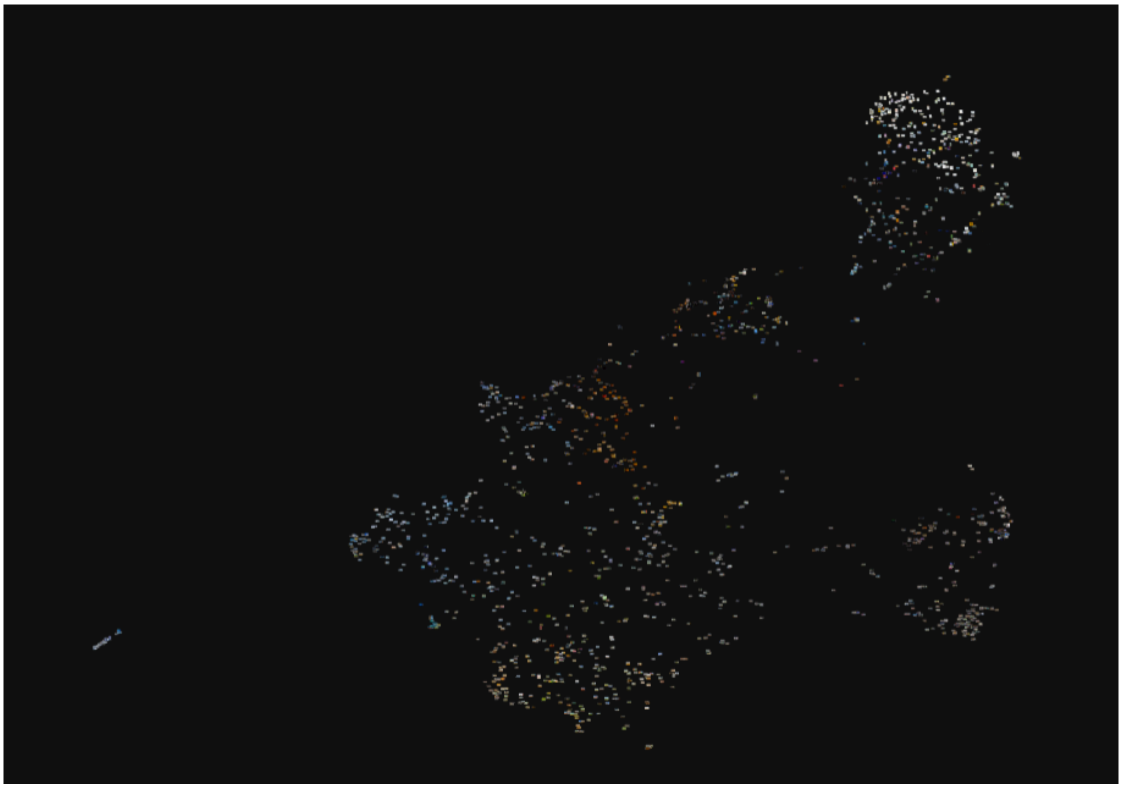


Figure 7. Image t-SNE of Locales Brazil as a whole.

Thus, far from any visual content, initial hypotheses about the composition of the visual landscapes could be detected on a structural level. For example, in the t-SNE of the search query for the Brazilian *locale*, a total of five image groupings could be identified: a very large and colourful one (centred), an isolated conspicuously dense and bright group (far upper right), two image groups of heterogeneous colourfulness (centred right and lower right), of which the centred one seems to merge into the large image group, and a conspicuously strongly isolated elongated and dense image group in the colour blue (lower left). 30

In addition, a very high similarity of the formation of the shape of the t-SNE visualization from the Australian image query with that of the USA could be found. Both image landscapes were similar in terms of density and distance or scatteredness as well as colourfulness of the image landscapes. It was reasonable to assume that despite different VPN tuning, these two *locales* were very similar in their Google image content due to the same language of search terms. 31

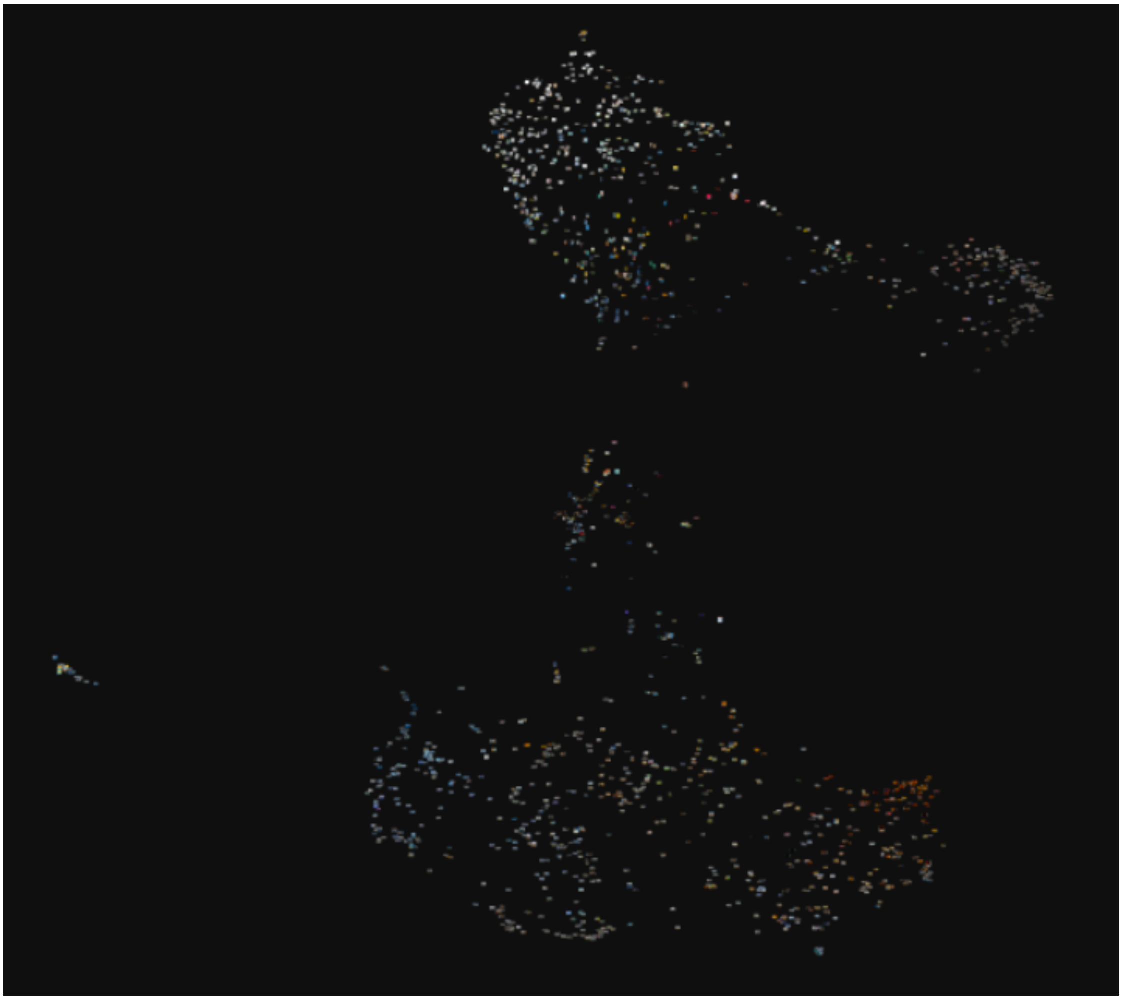


Figure 8. T-SNE visualisation of Australian Google image query.

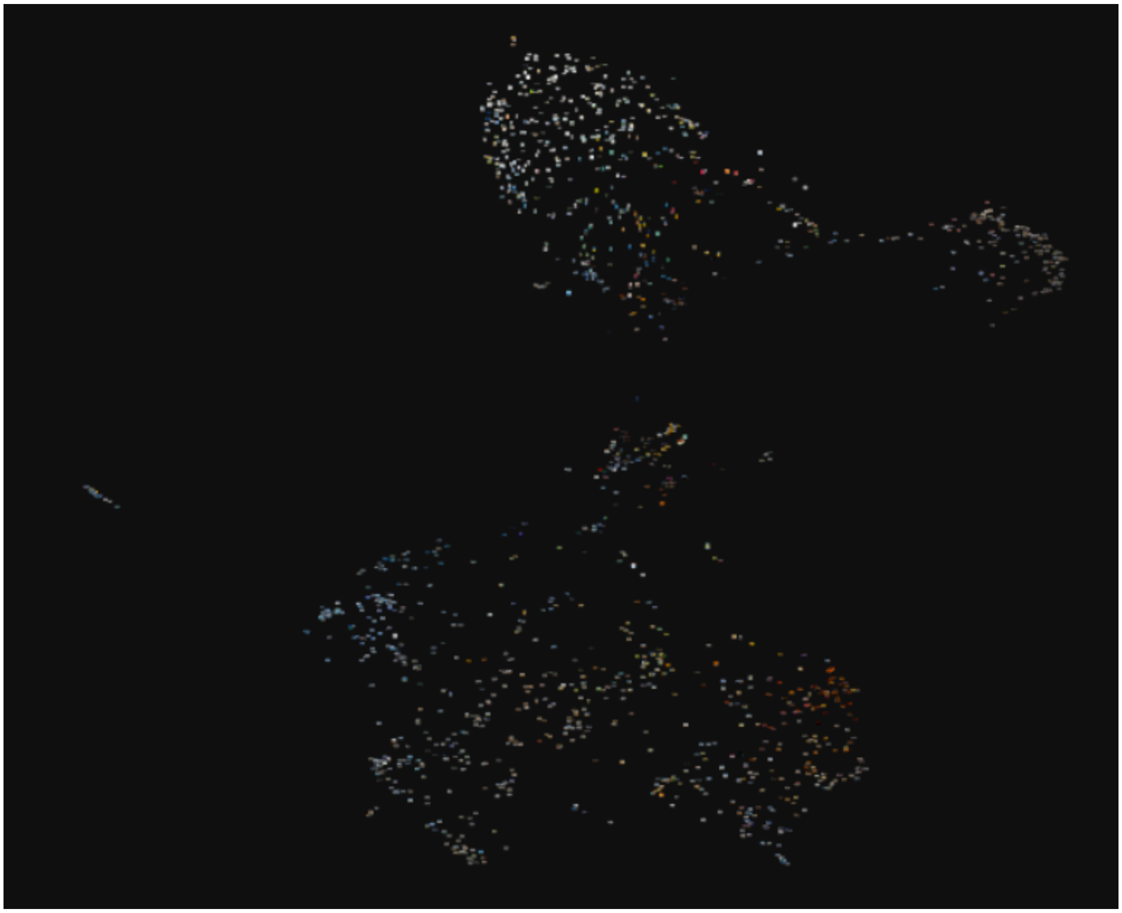


Figure 9. T-SNE visualisation of the American Google image query.

Due to the visual complexity of the t-SNE visualisations from a distance, an initial reading is based on *Gestalt*, as formulated by perceptual psychology or *Gestalt* theory. Perceptible were 32

- light-dark contrasts
- colour contrasts (white or coloured structures) and dominant colour structures,
- an interplay between the homogeneity and density of the image tiles and their heterogeneity and scatteredness.

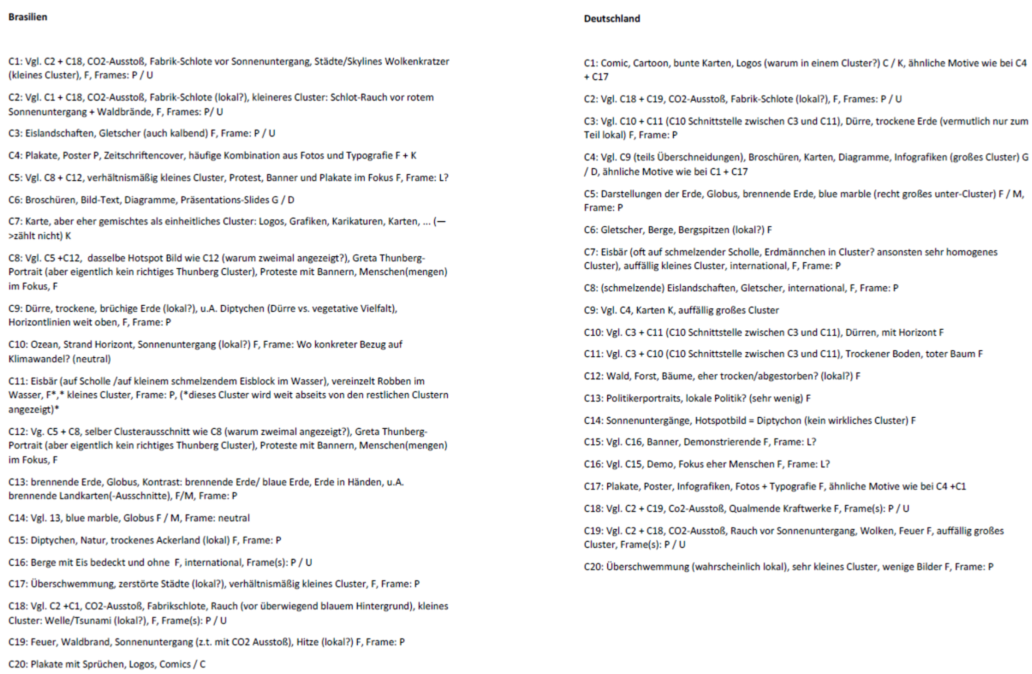
Thus, the three perceptual patterns already allowed a comparison of the country-specific t-SNE visualisations based on their different size ratios, colour occurrence, and homogeneous or heterogeneous distribution of images. 33

With regard to the evaluation of the similarity of the images among each other, hypotheses could be derived: The closer or denser the elements, the higher their commonality is interpreted. The more elements are condensed into groups, the more likely it is a common connection. This finding was expected after the description of the technical clustering. However, it can be emphasized because it is an expression for the actually invisible t-SNE-algorithm. Its logic of image sorting becomes perceptible and operable as cluster visualisation for content-related statements. 34

7 – Toggling as a digital image experience

On a qualitative level, the process of human perception of the climate images versus the automated pattern analysis of the machine learning algorithm was characterised by constant zooming in and out, a “toggling” process, within the country-specific interfaces [Schnapp 2012, 39]. In order to be able to compare the image clusters according to their size and their content, it was necessary to switch between individual images from a close view and the image landscapes from a distant view. The procedure of the distance view, if understood literally, offers the recipient an overview of the image collection and helps to recognise patterns and structures, but it stands in contrast to the individual viewing of 35 objects: “At the same time, distance views, due to their quantitative methods, are visually more abstract and more detrimental” [Dörk et al. 2020, 120].

Using toggling, the individual *hotspot* images were displayed by the machine learning algorithm as representative of a cluster in the visualisation and qualitatively indexed with terms. The twenty algorithmically evaluated *hotspots* were thus given a name according to human classification and interpretation of the image object. The qualitative naming of these *hotspots* served us as a first step to get to know the image objects and to be able to name them descriptively. It was done intuitively, but it was done iteratively by three different people. This is because the indexing partly demanded a uniform and general naming of the picture subjects or motifs (e.g., CO2 emission, polar bear, glacier), since these occurred repeatedly in the intercultural country queries. 36



Brasilien

C1: Vgl. C2 + C18, CO2-Ausstoß, Fabrik-Schlote vor Sonnenuntergang, Städte/Skylines Wolkenkratzer (kleines Cluster), F, Frames: P / U

C2: Vgl. C1 + C18, CO2-Ausstoß, Fabrik-Schlote (lokal?), kleineres Cluster: Schlot-Rauch vor rotem Sonnenuntergang + Waldbrände, F, Frames: P/ U

C3: Eislandschaften, Gletscher (auch kalbend) F, Frame: P / U

C4: Plakate, Poster P, Zeitschriftencover, häufige Kombination aus Fotos und Typografie F + K

C5: Vgl. C8 + C12, verhältnismäßig kleines Cluster, Protest, Banner und Plakate im Fokus F, Frame: L?

C6: Broschüren, Bild-Text, Diagramme, Präsentations-Slides G / D

C7: Karte, aber eher gemischtes als einheitliches Cluster: Logos, Grafiken, Karikaturen, Karten, ... (—>zählt nicht) K

C8: Vgl. C5 +C12, dasselbe Hotspot Bild wie C12 (warum zweimal angezeigt?), Greta Thunberg-Portrait (aber eigentlich kein richtiges Thunberg Cluster), Proteste mit Bannern, Menschen(mengen) im Fokus, F

C9: Dürre, trockene, brüchige Erde (lokal?), u.A. Diptychen (Dürre vs. vegetative Vielfalt), Horizontlinien weit oben, F, Frame: P

C10: Ozean, Strand Horizont, Sonnenuntergang (lokal?) F, Frame: Wo konkreter Bezug auf Klimawandel? (neutral)

C11: Eisbär (auf Scholle /auf kleinem schmelzendem Eisblock im Wasser), vereinzelt Robben im Wasser, F*,* kleines Cluster, Frame: P, (*dieses Cluster wird weit abseits von den restlichen Clustern angezeigt)*

C12: Vg. C5 + C8, selber Clusterausschnitt wie C8 (warum zweimal angezeigt?), Greta Thunberg-Portrait (aber eigentlich kein richtiges Thunberg Cluster), Proteste mit Bannern, Menschen(mengen) im Fokus, F

C13: brennende Erde, Globus, Kontrast: brennende Erde/ blaue Erde, Erde in Händen, u.A. brennende Landkarten(-Ausschnitte), F/M, Frame: P

C14: Vgl. 13, blue marble, Globus F / M, Frame: neutral

C15: Diptychen, Natur, trockenes Ackerland (lokal) F, Frame: P

C16: Berge mit Eis bedeckt und ohne F, international, Frame(s): P / U

C17: Überschwemmung, zerstörte Städte (lokal?), verhältnismäßig kleines Cluster, F, Frame: P

C18: Vgl. C2 +C1, CO2-Ausstoß, Fabrikschlote, Rauch (vor überwiegend blauem Hintergrund), kleines Cluster: Welle/Tsunami (lokal?), F, Frame(s): P / U

C19: Feuer, Waldbrand, Sonnenuntergang (z.t. mit CO2 Ausstoß), Hitze (lokal?) F, Frame: P

C20: Plakate mit Sprüchen, Logos, Comics / C

Deutschland

C1: Comic, Cartoon, bunte Karten, Logos (warum in einem Cluster?) C / K, ähnliche Motive wie bei C4 + C17

C2: Vgl. C18 + C19, CO2-Ausstoß, Fabrik-Schlote (lokal?), F, Frames: P / U

C3: Vgl. C10 + C11 (C10 Schnittstelle zwischen C3 und C11), Dürre, trockene Erde (vermutlich nur zum Teil lokal) F, Frame: P

C4: Vgl. C9 (teils Überschneidungen), Broschüren, Karten, Diagramme, Infografiken (großes Cluster) G / D, ähnliche Motive wie bei C1 + C17

C5: Darstellungen der Erde, Globus, brennende Erde, blue marble (recht großes unter-Cluster) F / M, Frame: P

C6: Gletscher, Berge, Bergspitzen (lokal?) F

C7: Eisbär (oft auf schmelzender Scholle, Erdmännchen in Cluster? ansonsten sehr homogenes Cluster), auffällig kleines Cluster, international, F, Frame: P

C8: (schmelzende) Eislandschaften, Gletscher, international, F, Frame: P

C9: Vgl. C4, Karten K, auffällig großes Cluster

C10: Vgl. C3 + C11 (C10 Schnittstelle zwischen C3 und C11), Dürren, mit Horizont F

C11: Vgl. C3 + C10 (C10 Schnittstelle zwischen C3 und C11), Trockener Boden, toter Baum F

C12: Wald, Forst, Bäume, eher trocken/abgestorben? (lokal?) F

C13: Politikerportraits, lokale Politik? (sehr wenig) F

C14: Sonnenuntergänge, Hotspotbild = Diptychon (kein wirkliches Cluster) F

C15: Vgl. C16, Banner, Demonstrierende F, Frame: L?

C16: Vgl. C15, Demo, Fokus eher Menschen F, Frame: L?

C17: Plakate, Poster, Infografiken, Fotos + Typografie F, ähnliche Motive wie bei C4 +C1

C18: Vgl. C2 + C19, Co2-Ausstoß, Qualmende Kraftwerke F, Frame(s): P / U

C19: Vgl. C2 + C18, CO2-Ausstoß, Rauch vor Sonnenuntergang, Wolken, Feuer F, auffällig großes Cluster, Frame(s): P / U

C20: Überschwemmung (wahrscheinlich lokal), sehr kleines Cluster, wenige Bilder F, Frame: P

Figure 10. Example of indexing the hotspot images from the t-SNE visualizations to the Brazil and Germany locales

8 – Cluster versus image group

In the designation of the *hotspots* and their technical image clusters, methodological differences between quantitative and qualitative clustering emerged that had to be considered for the further course of the qualitative image analysis: 37

- a) *Hotspot* images detected by the algorithm did not correspond to any or only a very marginal cluster in the sense of an image group according to qualitative assessment.

Methodologically, the question arose with regard to the t-SNE algorithm as to how the computer technically defines a cluster and thus also detects the *hotspot* image. As the hotspot image of Greta Thunberg from the Brazilian t-SNE visualisation, which occurred twice, showed, it was an image that qualitatively did not take on any status as an image group. Rather, the portrait of Greta Thunberg seemed to exhibit a high similarity factor precisely in its duplicity. 38

Figure 11. Hotspot image of Greta Thunberg from the Google search query of the Brazilian locale, which qualitatively does not correspond to any cluster.

- b) At the same time, the problem arose that some images, which qualitatively showed a high motivic similarity and evidence, were not detected as a *hotspot* by the algorithm. For example, the algorithm identified images of the Earth as a colour contrasting globe within the t-SNE visualisation of the *locale* Bangladesh as an *hotspot* image, while the same motif was merely a section of the general cluster of Earths within the t-SNE-visualisation of the Brazil *locale*.

Figure 12. Hotspot-cluster C13 from the Earth (burning) and the general Earth cluster, within which the Earth forms a section as a diptych and was subsequently qualitatively determined in the t-SNE-visualisation of the Brazil locale.

Accordingly, it can be stated that the determination of a t-SNE cluster technically does not necessarily result from a high 39
number of images, but due to a high similarity rate of sometimes only two images.

The German translation of the word cluster as accumulation or group therefore does not find its fundamental meaning 40
technically. We therefore used the word cluster as a technical term in the sense of the t-SNE clustering algorithm, the word image group as a qualitative determination of dominant motifs in their frequency. Thesis-wise, it can be stated on a technical level that the higher the similarity factor of the images, the more likely it is a technical cluster with a *hotspot*. The higher the similarity value, the closer the images tend to be to each other and the stronger the separation of the cluster from the rest of the image swarm. On the level of human perception, it can be stated that the higher the frequency of motifs with a common similarity criterion, the more likely it is to be an image group.

9 – Screenshot tableau

The distribution of denotatively determined main image content manifests itself through observable variation among 41
locales. We qualitatively created a screenshot tableau that sorted and contrasted the concise and central image clusters or groups of main motifs per *locale*. Methodologically, the systematic comparison of the 90 screenshot clusters was a quantitative process within the qualitative image analysis. As a procedure, the tableau in the form of a tiled overview allowed us to determine size distributions, commonalities, and differences among the clustered climate images.

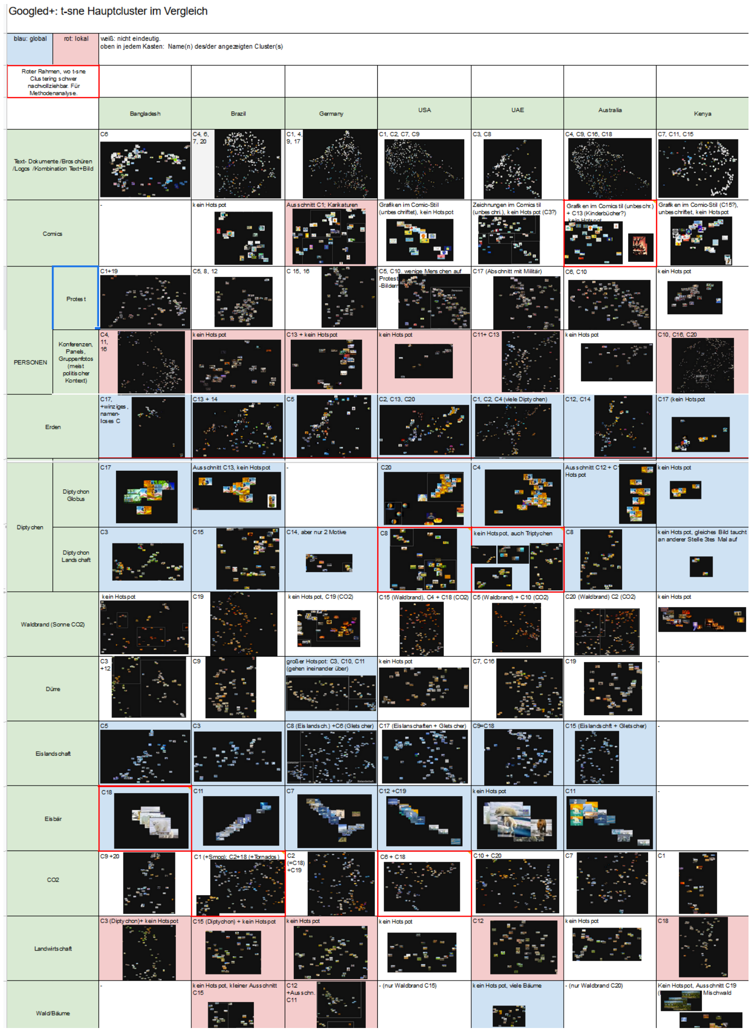


Figure 13. Screenshot table with image groups of the t-SNE

The determination of the group sizes only took place in the form of tendencies. The formation of the images according to iconographic similarity criteria is partially interrupted by the algorithm due to formal-technical structural differences. For example, the photographs of artificially created contrast representations diverged strongly in the visualisation of the Google images according to the U.S. American *locale*. While from a semiotic and iconographic perspective the green-orange contrast represents the symbolic and evidential similarity feature for the dichotomy of healthy versus dystopian climate futures, the algorithm separates this into two image clusters distant from each other by structural image properties (structure of the tree versus that of the landscape).

Figure 14. Formal-structurally separated image group of contrast photographs in t-SNE of US-American Google images, source of the single images: https://www.azocleantech.com/images/Article_Images/ImageForArticle_898(1).jpg (above), https://thumbs-prod.si-cdn.com/PKIvqzZfGkfhGDKTRxJ6_SodI1U=/420x240/https://public-media.si-cdn.com/filer/5c/cc/5ccc5513-30b1-41b3-96b7-41b88524ed3a/cambio-climatico.jpg (down)

Conclusion

In the previous critical description of our pipeline, the qualitative inscription and strong influence of the technical method 43
of machine learning by us as image researchers and due to 'external' software became clear. In contrast, the qualitative view of the evaluation regarding the location of image groups was strongly influenced by quantitative measurement and counting methods, such as in the creation of the screenshot table. Becoming aware of this difficulty of insight and technical complexity through the juxtaposition of different algorithms is an essential building block in this form of mixed-method and thus DH research. It is a circumstance that we will call *more-than-distant viewing* for our study, building on Franco Moretti's (2000) concept of distant reading and following Johanna Drucker's (2017) countering approach of “distant reading isn't.”

Discussion of the methods: potentials and limits

While our automated image analysis described here is based on machine learning, the algorithms are based on a 44
lengthy and highly qualitative interpretation and decision-making process. Thus, it became clear to us how our methodological approach and use of Google as an access point to the universe of climate imagery revealed more about current imagery occurrence in Google and how machine learning algorithms can be made applicable to our topic, namely culturally distinct climate imagery communication. The many preconceived technical standards and qualitative inscriptions inherent in any computational process became conspicuous at different levels and had a drastic effect on the entire research process, including qualitative image analysis. We conclude with citing four examples that illustrate this shift:

The basic parameterisation as a first step, for example, fundamentally shifted our research question. In our example, 45
the initially content-driven research question about the globalisation of the visual language of climate change became a formal description problem of how intercultural image communication can be made measurable in itself. Such research then describes not so much the actual object of research as the constraints and dynamics through abstraction for a numerical logic. This statistical description and reductionist ordering of the research object is the conceptual foundation for the so-called digital methods in general, because every computer-based process needs the concrete distinction and

knows no spaces in between.

In a second step, we had to curate our image corpus of a global climate communication. We are interested in mainstream image communication in cultural spaces and, therefore, deliberately decided on the largest possible, extensively used and highly formalized image space – Google Image Search. The so-called *PageRank* algorithm that orders the search results via Google Images was responsible for the type and diversity of climate images that we analysed. It is known that around 200 factors [Search Engine Land 2010] are influencing this algorithm, while some are known the most relevant are kept well hidden. This is why such a technical framework is often referred to as a *black box*. Ultimately, this means that we do not know the intrinsic ideas and models of the algorithms used and intentionally reproduce them. In the end, what we ultimately analysed was not a neutral perspective on climate communication, but the one shaped by google engineers. One open challenge, therefore, is how to deal with the obvious but undetectable biases of machine learning as a service applications. 46

Another challenge was the choice of algorithms for automated image analysis. We decided to use machine learning algorithms for similarity comparison due to the amount of climate images collected. This proved an important decision on several levels: On the one hand, the productivity and the pure image volume that can be processed were greatly expanded by automating the image analysis, as expected. On the other hand, the calibration (*training*) and data requirements of such machine learning algorithms are very expensive in acquisition and maintenance, and thus far exceeded the resources of our project. Therefore, we decided to use a pre-trained neural network called Inception v3 by Google, which was trained based on the ImageNet dataset. The concrete implications for the study are that the computed similarity between images is not based on a dataset explicitly designed for the climate imagery corpus, but is searched using a very generalist image corpus tagged with unknown motifs and models. In addition, the machine learning architecture makes it not impossible, but very difficult, to trace in detail the basis on which similarity relations between images were found. We know that such algorithms develop a structural view. We can thus deduce approaches, but not understand them in their entirety. 47

Finally, the choice of dimension reduction had a decisive impact on the qualitative reading of the visualisation. It decided on the definition of the *hotspots* as well as the image clusters and, connected to this, their reception in terms of content. The process of qualitative perception and interpretation of the various image clusters or groups turned out to be a challenging moment within the pipeline. In order to be able to make content-related statements about Google's intercultural climate image occurrence, it was necessary to permanently switch between distance view and close view. Thus, a purely quantitative reading suggested by the t-SNE technology and its visualisation could not be fulfilled. The quantitative influence that the automated image analysis had on the qualitative image analysis was unambiguous. For example, the indexing of the *hotspot* images manifested itself in a counting of recurring similar terms and their comparison among the *locales*. In addition, the creation of the screenshot table finally provided a measurement method to decompose the t-SNEs into comparable components, to design order tableaus, and to be able to make cross-cultural statements about climate image occurrence. 48

Through the examples summarised, it is clear that our approach evolved over the course of the study into *more than distant viewing* that profoundly changed the epistemic practice of image analysis. Here, the methodological combination of automated image analysis and qualitative reading of data visualisation manifests itself as a challenging yet productive method for examining large image datasets. The combination of machine learning and visualization offers an alternative to graph-based layout methods and an alternative to purely keyword-based image research, where clusters emerge via language alone. The approach helps in the search for framings and the exploration of images themselves. Ultimately, the following questions stood at the end: 49

Why are Google image search results so clichéd in the case of climate change? At the level of how climate change image searches differ in different regions and language areas, the following points need to be discussed further: Climate communication using images seems to be fairly standardised around the world. It was striking how many similar and identical images Google displays in each location. Each location has similar clusters such as polar bears, polar regions, or people at conferences. 50

When we look at a t-SNE visualisation, the question is: How do these images cluster? There is no automated method for detecting the clusters. We had no comprehensible criterion for the *hotspots* or for measuring the similarity of the images as what we eventually interpreted visually. Discrepancies between the qualitative determination of a group of images and the technical detection of the clusters by the algorithm became apparent. Similarity in the technical sense in the form of the *hotspots* does not guarantee the determination of a high number of related images. As we have seen, the term clustering as a hinge term between methodological approaches can even be confusing. Thus, it is better to understand *hotspots* as technical catch images instead of (qualitative) image groups. Regarding the t-SNE approach, we can recommend to mention the language use explicitly to be fair to the concepts of the different disciplines. 51

To what extent do human and automatic image recognition differ in image sorting? At first glance, it can be stated that humans tend to sort images according to motifs, while algorithms sort images according to structure. This became particularly clear in the form of a workshop in which we as a research team developed a section of the Google image corpus' on the German *locale* (550 images) as photographs and sorted them by hand. The sorting was intuitive and based on themes and motifs. In doing so, unlike the t-SNE algorithm in physical space, we did not set distances between image groups, since we did not know at the outset how many images would belong to each image group and since the size of the floor was limited. The efficiency of the technology to manage huge amounts of images was clearly felt here. The colour distribution of the manually created t-SNEs was a result of the image themes, while the algorithm sometimes blew up content-related image correlations due to different colour patterns. It nevertheless came out surprisingly that the human image selection converged with that of the t-SNE in terms of clustering the dominant image groups (drought/dry soil, heat/fire, earths, CO2- refineries, maps, cartoons, etc.). This is significant because the process of creating t-SNE visualisations from the source images does not extract semantic information from the dataset. 52

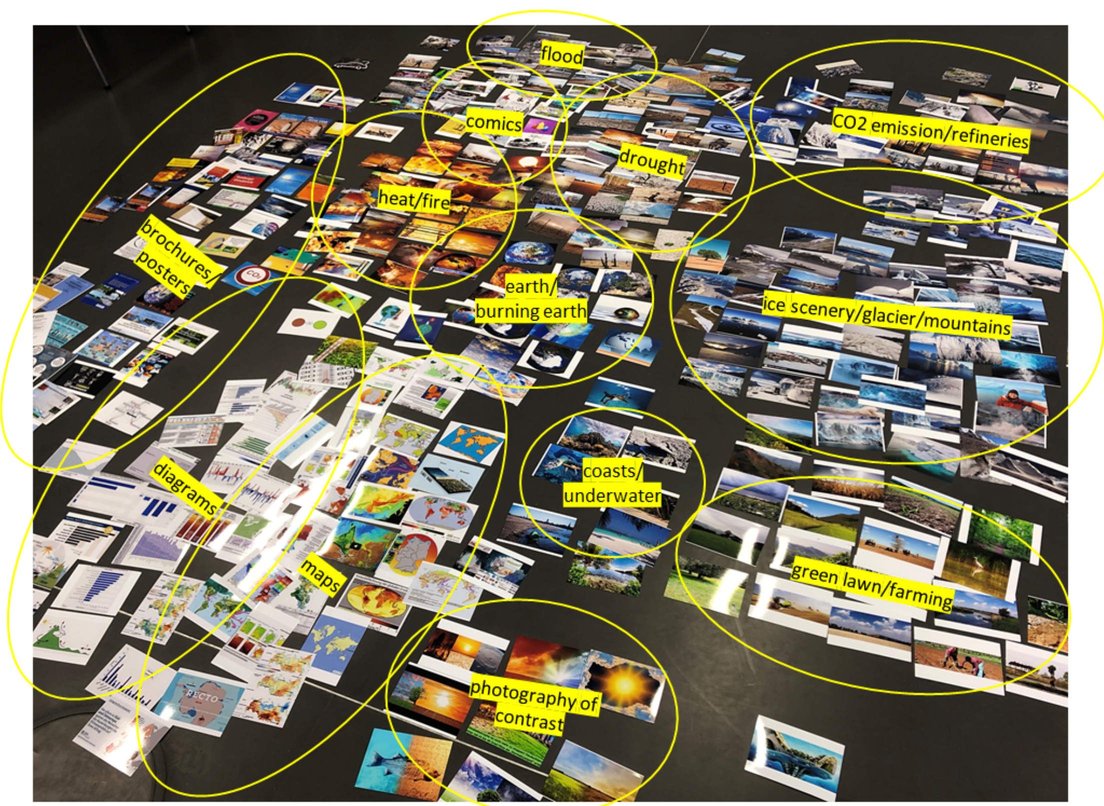


Figure 15. Manual image sorting of photographic prints to the dataset of the German locale with annotations

Outlook

In conclusion, further research and in-depth arguments are needed to understand the full implications and scope of the use of automated image recognition in order to make a sound argument about the methods described. For example, Google image ranking and the logic of the PageRank algorithm, i.e., the images Google ranks on websites, need to be 53 examined: Where exactly does the image corpus come from? Who supplies the images to be found? Are there some globally ubiquitous sources? Working with machine learning in the context of the Digital Humanities also needs to be questioned, especially on an infrastructural level. This is because working with datasets depends on software companies. There are few and large tech companies able to offer their pre-trained algorithms (often free and freely available). Reflection on the worldviews and values inscribed in them must not give way to strong fascination with technical productivity. In general, considering the qualitative moments in automation and the quantitative aspects in analysis according to our model of 'more than distant viewing' is an elaborate and laborious investment, but ultimately rewarding for the research process.

Notes

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