

**Pratt**

**Goldsmiths**  
UNIVERSITY OF LONDON

# THE MUSEUMS + AI NETWORK

---

AI: A Museum Planning Toolkit

Dr Oonagh Murphy  
Dr Elena Villaespesa



# CONTENTS

<b>Introduction</b>	1
<b>Thinking about AI</b>	2
<b>Case studies</b>	
American Museum of Natural History	4
The National Gallery	6
The Metropolitan Museum of Art	8
<b>Worksheets</b>	
AI Capabilities	10
AI Ethics Workflow	12
Stakeholder map	14
<b>Glossary</b>	15
<b>Acknowledgements</b>	21
<b>Notes</b>	22

First published January 2020  
By Goldsmiths, University of London,  
New Cross  
London SE14 6NW

ISBN (Print) 9781913380212  
ISBN (Electronic) 9781913380229

Authored by:  
Dr Oonagh Murphy, Goldsmiths, University of London  
Dr Elena Villaespesa, Pratt Institute

Additional contributions by:  
Luba Elliott, Ariana French, Jennie Choi, Casey Scott-Songin



Academic Partners:



The Network is funded by:



# INTRODUCTION

The Museums + AI Network was formed in 2019 by Dr Oonagh Murphy, Goldsmiths, University of London and Dr Elena Villaespesa, School of Information, Pratt Institute. The network was funded through the AHRC Research Networking Scheme and so far has brought together 50 leading academics and museum professionals to critically examine current practice, challenges, and near future Artificial Intelligence (AI) technologies in both the United Kingdom and United States. The network has also engaged with more than 200 members of the public through events at Cooper Hewitt, Smithsonian Design Museum (New York) and The Barbican Centre (London).

Through these conversations, workshops, and public events we challenged current practice, engaged with wider critical technology discourse and iteratively developed a series of worksheets with professionals from 15 museums, and 6 universities in both countries. We also engaged with policy makers and funders as a means to situate these development tools within a wider cultural policy context.

This toolkit distils some of these conversations, flags areas for critical engagement, and serves as a practical starting point for museum professionals who are interested in working with technologies that fit within the broad field of Artificial Intelligence. The aim of this toolkit is to support non specialists to better understand the possibilities of these technologies, and empower a wide range of museum professionals to develop - strategically, ethically, and operationally robust project plans.

While developing this toolkit we have been approached by museums who would like support in understanding the possibilities of AI, clarification on key terms and an overview of the key things to consider when thinking about AI. This toolkit seeks to begin to answer those queries. It is designed to start a conversation. Conscious of the fast moving nature of this field we decided against the inclusion of a definitive how to guide, but instead sought to provide space for critical reflection, and in some ways we offer more questions than solutions.

**[themuseumsai.network](https://themuseumsai.network)**

# THINKING ABOUT AI

When considering using AI technologies, museums need to think about the potential benefits and challenges such technologies present. This list frames some areas for consideration, however each museum exists within a unique context, and as such this list is intended as a jumping off point, from which to explore projects and partnerships with your wider team before a project has been fully costed, or funding sought for implementation:

## Why AI?

The conversation around AI is often over simplified, with many technologies that fall within this conversation falling far short of having sentient intelligence, instead what we see is advanced algorithmic decision making. As such it is important to not only understand the technology you intend to use, but also what data it will require (as input) and what data it will generate as output. As with most 'new technologies' it can be appealing to engage with world leading companies, and become innovators of museum practice. However as previous trends from Apps to 3D printing have shown us, the best technology provides solutions to questions or challenges faced by a museum, rather than existing as an additional layer to a museums core mission. Technology used well helps to further your mission.

## Just because it's legal doesn't mean it's ethical

Regulation in the UK and US around technology is somewhat lacking, and as such many technology solutions from facial recognition to algorithmic decision making are legal, but ethically questionable. Museums, as social purpose institutions must reflect upon their professional standards, alongside the law when it comes to developing and implementing AI technologies. Professional standards when it comes to digital practice in museums are perhaps best described as interdisciplinary with many of those working in digital departments coming from computing

backgrounds, rather than museology. As such, engaging with a wide range of professional standards can help to inform nuanced practice that aligns to the mission and values of your museum.

Relevant codes of practice include:

- Museums Association - Code of Ethics for Museums (UK)
- American Alliance of Museums - Code of Ethics for Museums (US)
- Chartered Institute for Archaeologists - Professional Practice Paper: An Introduction to Professional Ethics (UK and International)
- International Council of Museums - Code of Ethics for Museums (International)
- Association for Computer Machinery - Code of Ethics and Professional Conduct (International)

## Off the shelf tools

A number of AI tools can be used for free, or cheaply (often through a freemium model), these range from IBM Watson a natural language processing tool that allows you to analyse vast amounts of text based data, such as visitor feedback, quickly and cheaply. Or, machine vision tools such as Google Cloud Vision API, or Microsoft Azure which allow you to create metadata tags for images, something that can be useful when it comes to managing vast digitised collections. These 'off the shelf' tools are likely to become more sophisticated in the coming years, and as such more commonly used. However in order for museums to engage with such technologies in a manner that aligns with their mission, they need to be conscious of quality assurance and bias management.

## Quality Assurance Process

### - Human Augmentation

When using any computational decision making tool it is important to have human quality assurance processes in place. Exploring what this process may

look like, will help you to reflect upon the data created through AI tools, and how that data will be used internally, but also externally. Will the data be visitor facing? What are the implications of creating visitor facing data?

## Bias management

Machines much like museums are inherently biased, as such whilst machine learning tools may provide valuable metadata for your online collection it could also create bias squared (museum bias x machine bias). As such understanding the training data used to teach the machine, and the algorithms used to make decisions are crucial to ensure the integrity of any application of these technologies within museums.

## Brandwashing

Technology companies are keen to work with museums, particularly large museums with strong national and international brands. This can provide museums with access to cutting edge technology, custom built solutions (which can be much more effective than off the shelf tools), and support in kind from technology professionals. However, museums need to think about such partnerships in the same way that they do fundraising. What are the ethical implications of brand affiliation with a specific tech company? How does that relationship align with the mission of the museum? What are the potential unintended consequences of such a partnership?

## Critical Technology Discourse

While some issues raised in this toolkit may sound problematic, these technologies are increasingly being used in wider society. Museums have an opportunity to critically engage with these technologies and the impact they have, by being open and accountable about what technologies they are using, and through public programs and contemporary collecting to develop visitor literacy around AI

and Machine Learning Technologies. The Photographers Gallery in London has a strong critical technology discourse theme across much of its public programming, while the V&A has begun to collect AI technologies and associated art, such Anatomy of an AI System, by Kate Crawford and Vladan Joler (2018). The link between what happens in the digital team, public programs, and collecting could become more reflective and engaged through organisation wide transparency, dialogue and development.

## AMERICAN MUSEUM OF NATURAL HISTORY (US)

Founded in 1869, the American Museum of Natural History (AMNH) is the largest natural history museum in the world. The museum is located on the Upper West Side in New York City, and welcomes tourists visiting the city, along with local residents, educators, researchers, and school groups. The museum hosts approximately 5 million visitors annually.

### Visitor surveys and comments analysis

The AMNH is reviewed by visitors on a range of different online platforms during and after their visit to the museum, one of the challenges for the museum is analysing these reviews in a timely and cost effective manner. The museum emails a survey two days after a visit (using the contact details provided when the visitor was purchasing an admission ticket). The survey asks a quantitative question 'How likely are you to recommend the American Museum of Natural History?' and visitors are invited to select a numerical value between 1 and 10. The data created in response to this question is straightforward to analyse on mass, however, the follow up question which generates a qualitative response is more challenging: "What is the most important reason for your score?" As a cost-effective way to explore if NLP could provide new insights into visitor feedback, AMNH decided to use an off the shelf Natural Language Processing (NLP) and sentiment analysis service created by a commercial vendor.

IBM Watson is a platform that allows users to identify and analyse a range of concepts, categories, relationships, emotion and sentiment within vast quantities of qualitative data. Its NLP suite of services can be used to generate sentiment analysis reporting on a specific subset of words, or entities. For example,

AMNH used commonly mentioned words in NPS survey comments to more closely examine the sentiment associated with those words.

The above sentiment and entity analysis is a proof of concept, developed with six months of NPS survey comments data. The free tier of IBM Watson's sentiment analysis service was used to analyze these entities and associated sentiment scores.

### Google Cloud and TripAdvisor

Google's Cloud Natural Language Processing API provides a similar service to the IBM Watson NLP sentiment services, which AMNH used to analyze reviews shared on the TripAdvisor platform. Tens of thousands of reviews were used as input data to Google's service, and sentiment analysis scores and popular named entities were included in the service output.

A general sentiment score, ranging from -1 (very negative) to +1 (very positive) was generated for the top 7 museums (by attendance) in the USA. With a score of 0.5, the National Air and Space Museum and the Natural Gallery of Art scored highest, followed by museums with a score of 0.4: American Museum of Natural History, the Metropolitan Museum of Art, National Museum of American History, National Museum of Natural History, and 9/11 Memorial Museum. Additionally, AMNH used Google's NLP service to extract the most popular named entities within TripAdvisor reviews to gain insights into what visitors mentioned most frequently within reviews.

### Potential challenges

Whilst AI provides a valuable starting point when it comes to engaging with large amounts of qualitative data, providing appropriate context and

interpretation is still the job of humans. Those working in museums and with visitors can provide a valuable layer of analysis that can add to the validity and operational insights provided by these commercial services.

### What can we learn from this case study?

An off the shelf cloud service such as IBM Watson or Google Cloud Natural Language Processing can be a cost-effective way to analyse large amounts of qualitative data and extract focused insights on visitor sentiment and aspects of the visitor experience.

### Useful links

<http://www.ibm.com/watson/>

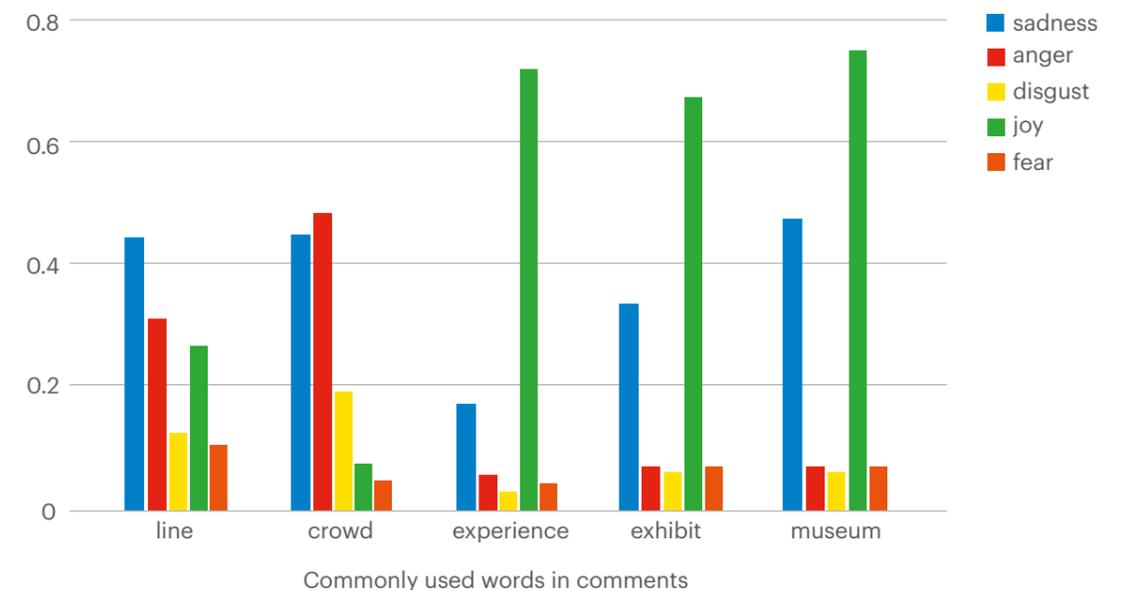
<http://cloud.google.com/natural-language/>

<http://medium.com/@CuriousThirst/on-artificial-intelligence-museums-and-feelings-598b7ba8beb6>

### Artificial intelligence featured in this case study: Natural Language Processing (NLP)

Below: This chart shows the insights provided IBM Watson

### Sentiment analysis of NPS survey comments (sample)



## THE NATIONAL GALLERY (UK)

The National Gallery, London was founded in 1824 and today boasts a collection of over 2,300 paintings, including some of the most important works from the 1300's to 1900. The museum is free to enter, and many galleries are free to visit. One area of the museum does command an entrance fee, namely, temporary exhibitions. The museum has a dynamic temporary exhibition programme which brings together works from its own collection and the finest examples of painting from other leading collections. In 2018, the gallery had 5.7 million visitors, of which 8% attended temporary exhibitions.

### Machine learning, forecasting models and visitor data

One of the challenges for The National Gallery is predicting the capacity required by potential demand for temporary exhibitions. This includes the physical capacity of an exhibition space (how many people can comfortably fit within a gallery? And if an exhibition is likely to be popular, is the allocated gallery space enough?), but also resource capacity (how many tickets will be sold for a specific exhibition? what time slots and days will be busy or quiet? and, what type of people will visit the exhibition?) The answers to these questions can help the museum to create a more enjoyable visitor experience and more financially viable exhibition prospect for the museum.

The Data and Insights team at the National Gallery have been developing custom built predictive models as a means to answer some of these questions. These include forecasting potential attendance about 12-18 months before an exhibition opens; and once an exhibition has been open for 3 weeks a daily forecast for overall attendance as well as paid tickets (excluding membership and comp visits)

After initial investigation, it was found that using the following factors as variables allowed a reliable forecasting model to be created:

- Whether an exhibition is thematic or monographic
- Movement and period of the art
- Page views of the artist's Wikipedia page
- The likelihood of the UK public to visit a paid exhibition by this artist (from commissioned YouGov survey)
- Length of exhibition
- Marketing spend on an exhibition
- Visit date (for daily forecast) or time of year (for total attendance forecast)
- Distance through the exhibition's run and sales period (for daily forecast)
- Day of the week (daily forecast)

The forecasting models use training data from over twenty years of exhibition history (less for daily models) and are created using gradient boosted tree based methods. The results are then integrated into an analytics dashboard that provides a detailed picture of ticket sales, attendance patterns, and revenue generation that is available for any employee to access.

### Predictive analytics as a provocation

The forecast is then used as a provocation to a range of departments from curatorial to marketing; it becomes a way of reflecting on if the current plans will deliver the intended results. Because the model is trained on historical data from exhibitions with similar artists or themes, it predicts how an exhibition might perform with certain audiences if similar tactics are planned for future exhibitions. These insights are utilised after an exhibition has been commissioned (and as such

have no input into the content of the temporary exhibition programme), but instead are introduced at the exhibition planning stage. Such data can influence ticket prices, exhibition location, exhibition calendar, exhibition run time, and marketing activities. If the data shows that the exhibition is not likely to appeal to a specific market then they can design marketing activities that will help peak interest within the target market. In the future such insights may also be used to influence staffing patterns for exhibitions, or create dynamic ticket pricing to prevent peak times and quiet times and ensure a more consistent visitor experience. The ultimate aim of this activity is to increase the quality of visitor experience (and as such drive repeat visits) and sculpt new audiences by targeting marketing messages to specific groups.

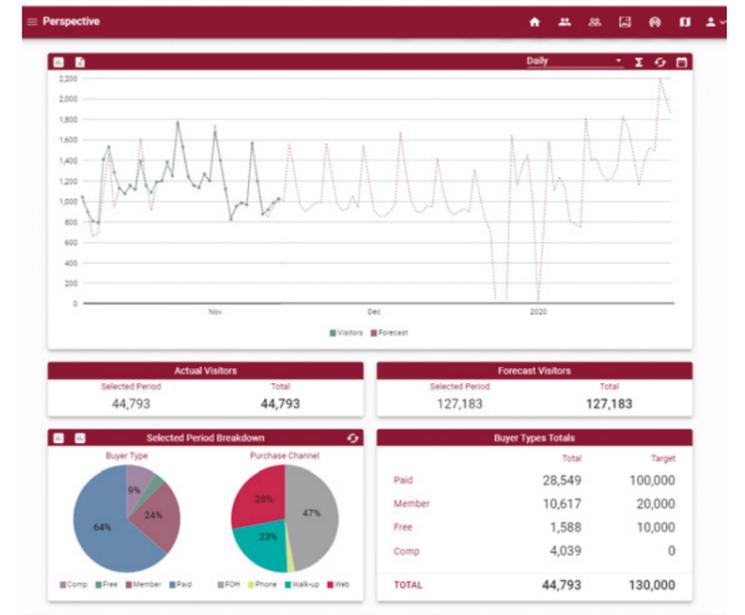
### Potential challenges

The insights provided by data must be viewed within the wider mission of the museum as an institution. Whilst busy exhibitions is one metric of a successful exhibition, scholarship, critical thinking and dialogue between cultures and art form are also central to the work of The National Gallery, and as such visitor experience and revenue form only one part of a complex operating context.

### What can we learn from this case study?

Quick implementation is possible: the team were able to develop initial working models within a few months, and with access to over ten years of exhibition data, they are able to continually develop their models to be increasingly accurate.

Further, the visibility of such models led other departments within the organisation to find their own uses for forecast data. This has led to success in buy-in and implementation across the Gallery and some Gallery staff have even reported that they feel empowered



Above: Screenshot of the predictive analytics dashboard used by the National Gallery

by the ability to use forecasting data to make data-informed decisions.

Forecasting can serve as a useful provocation to encourage changing organisational behaviours, it provides data driven insights to strategic decision making processes that can ultimately create more successful exhibitions (even when we consider a wide range of success metrics from those defined by curators, to those defined by visitors through to funders).

### Artificial intelligence featured in this case study: Machine Learning

## THE METROPOLITAN MUSEUM OF ART (US)

The Metropolitan Museum of Art opened for the first time to the public at its current site on Fifth Avenue and 82nd Street (New York) in 1880. It expanded to The Met Cloister in 1938 and The Met Breuer in 2016. The museum hosts approximately 7 million visitors annually. The museum currently contains more than 450,000 digitized records—and is growing in number with each passing week. Major collections belonging to the museum include American paintings and sculpture, European paintings, Egyptian art, arms and armor, the art of Africa, Oceania, and the Americas, ancient Near Eastern art, Asian art, costume, drawings and prints, European sculpture and decorative arts, Greek and Roman art, Islamic art, medieval art, modern and contemporary art, musical instruments, photographs, and the Robert Lehman Collection.

### Providing access to the Collection

With such a large and diverse collection, an ongoing challenge faced by staff at The Met is developing new ways to document, and interpret the museum's collection in a way that will allow it to become searchable and browsable

online. Many objects that have been digitised have very little information to support them, which means that whilst a digital image may exist, a lack of metadata or keywords prevent a user from being able to discover these items through search. The museum is working on the generation of tags manually and testing with computer vision. The goals of tagging the museum collection are to increase user engagement, improve search and discovery of the collection, make the collection accessible to the widest possible audience and explore using tags as training data for AI models.

The museum has manually tagged 233,000 objects from the collection working with an outside vendor. There are 1000 unique tags that were added using a single judgment. Moreover, the museum has engaged with different communities including Wikimedia, Kaggle, MIT and others to develop potential usages of this tagging work. The museum has also tested the usage of various computer vision technologies including Google Vision and Microsoft Azure to generate tags automatically.

### Potential challenges

There are significant challenges in the process of developing tags both manually or automatically with computer vision. The first challenge is imperfect training data which produces issues around subjectivity of the tags added, completeness of all the potential objects and items to be tagged, accuracy and relevance. There is not enough data within the collection itself to train the algorithm, as this normally requires thousands of records. In the case of the Met, more than half of the tags have less than 1000 occurrences, as such working with vendors and off the shelf systems has been crucial for this work to develop.

Another significant challenge is the implementation of the tags both into the collection management system and on the website user interface. Developer resources are needed to bring these keywords to the users so they can be searchable and clickable on the online collection.

### What can we learn from this case study?

AI has a lot of potential for making art more accessible to the public. Computer vision has come a long way and continues to improve making the enormous task of tagging museum collections a relatively simple process. However, museum collections are inherently biased and there are no right answers for tagging art. Therefore, museums need to offer a way of signifying the user that the tags have been generated by a machine with all the implications that this process brings. While museum datasets are not complete enough to train algorithms potentially museums could work together to produce an algorithm that could be applied in the sector. There is also an opportunity for museums to partner with the data science community to create machine learning models based on smaller datasets specifically for art objects.

### Useful links

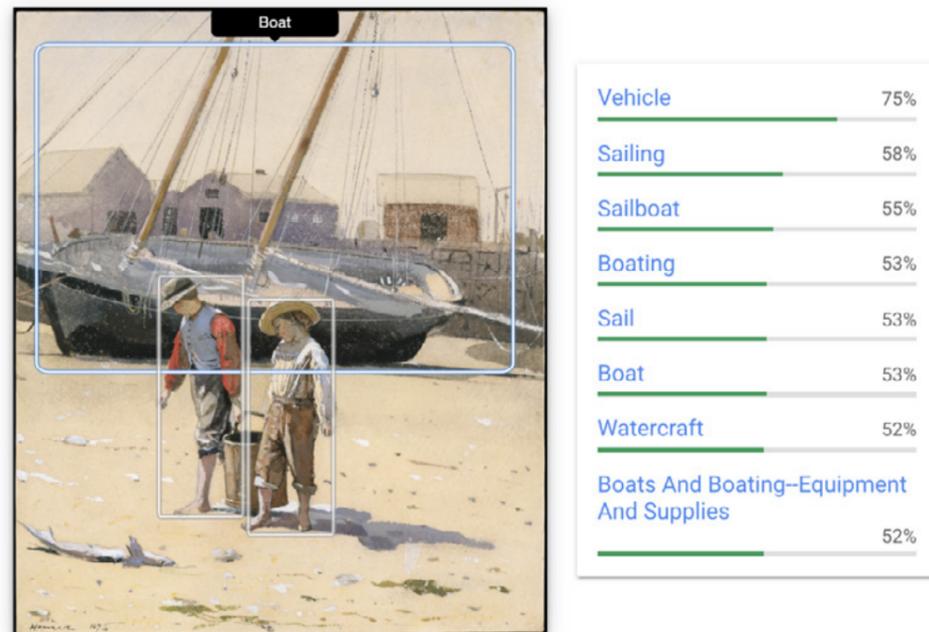
<http://www.metmuseum.org/blogs/now-at-the-met/2019/met-microsoft-mit-exploring-art-open-access-ai-whats-next>

<http://www.metmuseum.org/blogs/now-at-the-met/2019/wikipedia-art-and-ai>

<http://www.metmuseum.org/blogs/now-at-the-met/2019/artificial-intelligence-machine-learning-art-authorship>

<http://cloud.google.com/blog/products/gcp/when-art-meets-big-data-analyzing-200000-items-from-the-met-collection-in-bigquery>

### Artificial intelligence featured in this case study: Machine Vision



Above: Screenshot of what the machine saw when it looked at a painting from the collection

# WORKSHEET

## AI CAPABILITIES FRAMEWORK

An AI project requires resources and skills to gather, train and implement the data results. The goal of this worksheet is to discuss each of the following aspects of the capabilities needed to undertake this AI initiative.

### Data

- What is the data that will be used for this AI initiative?
- How should the museum be prepared in terms of data infrastructure and governance?
- Is there an ethics committee in place at the museum to assess and oversee the compliance of this project?

### Tools

- What are the AI methods and tools that would be employed?
- Would the museum use any external tools from technology companies?
- Are there open-source tools available for this AI project?

### Resources

- What are the required resources? (Human, Financial, External Collaborations, Technological)
- What is the project legacy? What is the technical debt that needs to be considered?

### Skills

- What are the skills museum staff need to work on this project?

### Organization

- Which museum departments need to be involved?
- What is the ideal workflow and process to implement this AI initiative?
- Is the museum's organizational culture ready for this initiative?

### Stakeholders

- What internal and external stakeholders would be invested in this project?
- How do you manage and communicate with the stakeholders?
- How do you foster early concept buy-in?

### Project title

### Project aim

### Data



### Tools



### Resources



### Skills



### Organization



### Stakeholders



## AI ETHICS WORKFLOW

AI brings a set of ethical implications and algorithm biases in each step of the initiative life cycle. The goal of this worksheet is to map the potential ethical issues and challenges that arise in each of the phases of an AI initiative from the data collection to the training, application and evaluation of the results.

Here are some questions to guide your discussions:

### Data input: Collection & clean up

- Is there bias already in the original dataset? What data is not represented?
- What is the process to clean up the data?
- Has informed consent been gathered for this data?  
Is there any personal information?
- What are the museum processes to store and keep this data secure?  
Does the museum comply with the legal data privacy requirements?

### Data training

- Do museum collections serve as valid training datasets?
- Is there enough data? What data is missing?
- Can we train a machine to see like a curator? What are the benefits and drawbacks of using machines?

### Testing/Model development

- What are the potential biases that these algorithms originate?
- What are the ethical implications of using third-party AI platforms to develop our model?
- Is there transparency in the model development process or is it a 'black box'?

### Application

- How will the 'black box' alter curatorial practice?
- What are the intended and unintended consequences of the application of this model?

### Data output

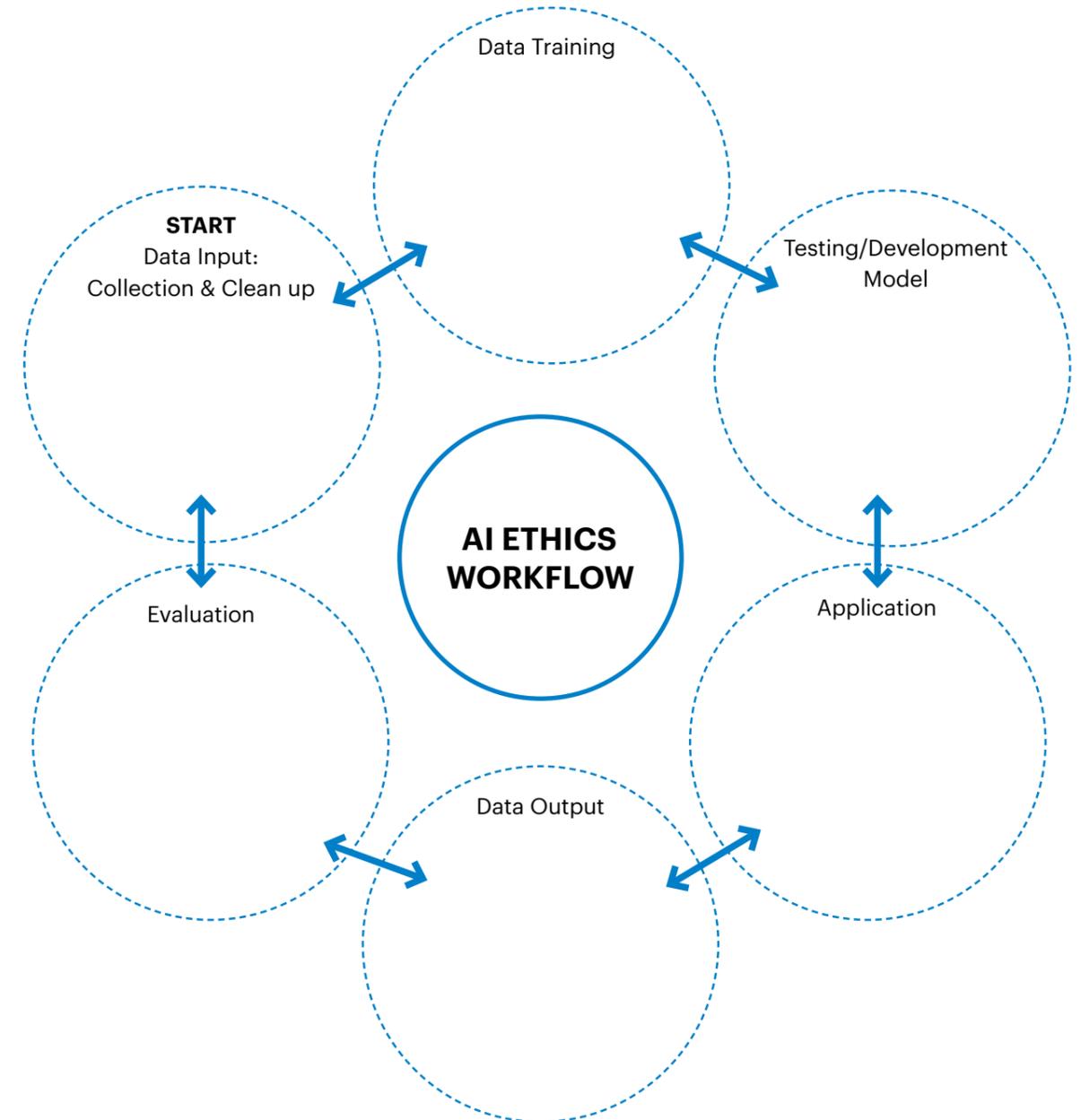
- Is there a potential bias in the data output?
- Can the process be documented and explained to users?
- What are the legacy and future applications of this data?

### Evaluation

- How does the museum evaluate the success of this AI initiative?
- What is the impact on the visitor experience?
- How does this work enhance and expand the collection data?
- How do the results of this project comply with the code of ethics of the different museum associations?

Project title

Project goals



## STAKEHOLDERS MANAGEMENT

AI projects involve many different partners, and it can be useful to map these partners or stakeholders at the project development stage. The goal of this worksheet is to think about everyone involved, interested and influential for your project. We suggest listing each person on an individual post-it note.

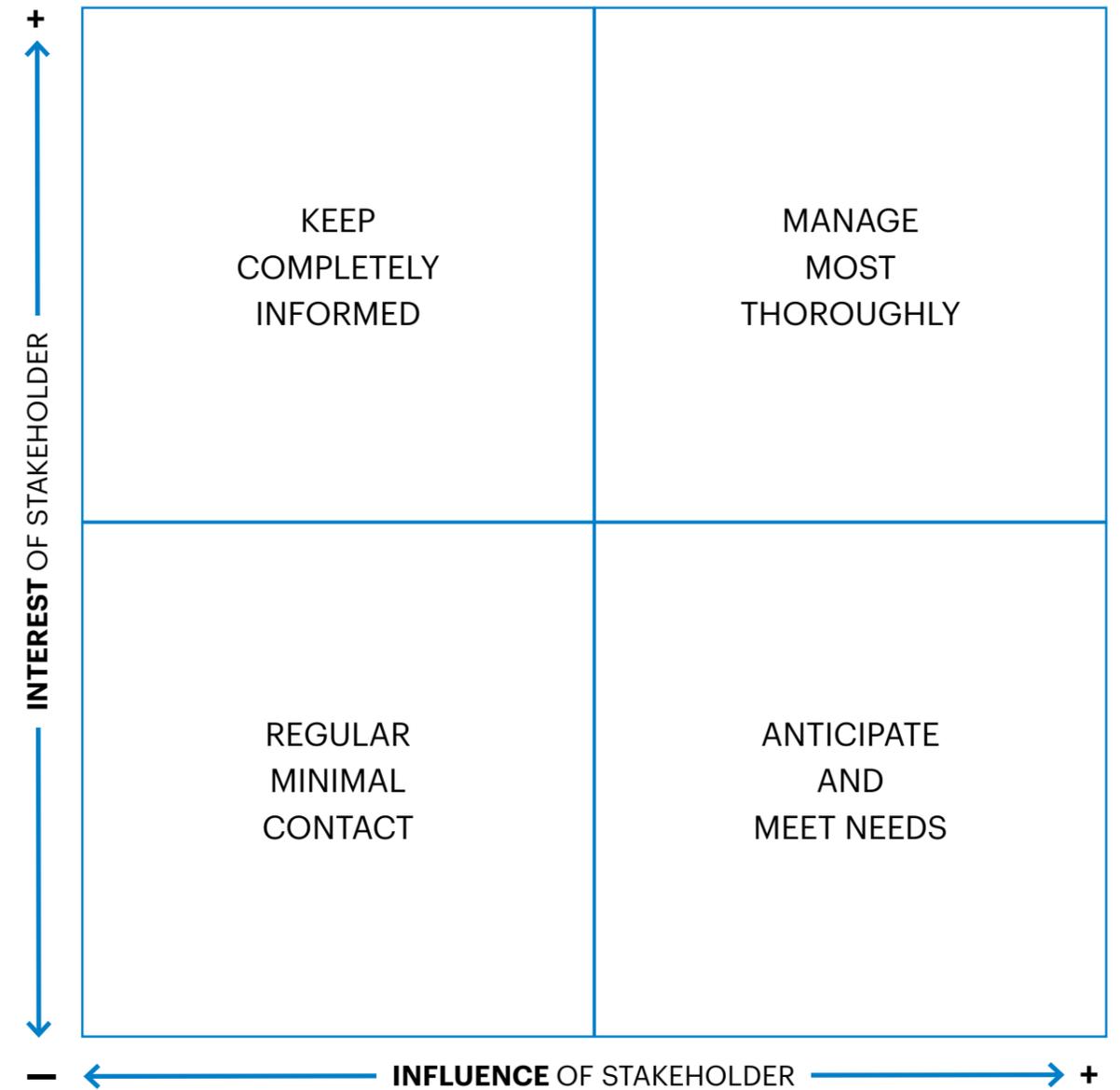
**Criteria:**

- Who will benefit from this AI initiative?
- Which internal stakeholders will need to support and contribute to the initiative in order to implement it? Are there any specific areas of resistance within the museum?
- Who owns and manages the data that will be used?
- Who in the museum leadership would need to know about this AI initiative?
- Are there any external stakeholders that will participate in this project or where conflict of interest may appear?
- Who would you need to involve to ensure data privacy and ethical practices for this AI initiative?

When you have listed all stakeholders, as a group discuss where they sit within the stakeholder mapping grid, and from there think about when and how you will communicate with each stakeholder.

## STAKEHOLDERS MAP: WHO NEEDS WHAT?

Project Title:



Adapted from Mendelow (1991)

**Algorithm**

An algorithm is a series of step by step instructions on how to perform a specific task. In computer science, different types of algorithms are used to recognise objects, translate between languages, recommend products and generate text. In many cases, multiple algorithms are combined to execute some of the more complex tasks. Algorithms are now being used in justice settings to determine prison sentences, and in financial contexts to create mortgage and insurance policies tailored to individuals based on their data footprint.

**Algorithmic bias**

Algorithmic bias refers to systematic errors in a computer system that create unfair outcomes, for example privileging one group of users over another. Bias can arise due to a number of factors, such as algorithm design, unintended applications or the way data is collected, coded, selected or used to train the algorithm. Impacts of algorithmic bias range from privacy violations to the amplification of social biases of gender, race, ethnicity and sexuality, which can lead to systematic and unfair discrimination in a wide variety of situations including prison sentencing, mortgage approval rates and healthcare premium calculations. In a museum context, algorithmic bias can manifest itself through inherent biases in museum collections, datasets and computer software applied to collection research and public engagement. An example of an art project highlighting bias in datasets is Kate Crawford and Trevor Paglen's ImageNet Roulette, which classifies a user's photo according to the popular ImageNet dataset. The resulting classification frequently gives unexpected and problematic results, particularly when used by people from Asia and Africa – groups which may have been underrepresented or labelled unfavourably in the original dataset.

**Black box**

A black box model is a system whose internal mechanisms are unknown. In machine learning, "black box" refers to a model which cannot be understood from its parameters: data goes in and decisions come out, however the process between input and output is unclear. This is particularly the case for neural network models, where input data can go through many transformations in the multiple layers of the neural network or where complex models can behave in unpredictable ways. The black box nature of many machine learning models is problematic because of their widespread application, giving rise to cases where individuals may be offered higher insurance premiums or denied mortgages based on the decision of the algorithm, which then cannot be explained. In the past couple of years, there have been increased efforts to develop more interpretable machine learning models, where the algorithms provide some justification or explanation for their decisions.

**Chatbot**

A chatbot is a computer program that is designed to mimic a human interaction in a text based conversation. These can be a useful tool for engaging with visitors on social media when a museum is closed, for example a Facebook Messenger Chatbot can answer simple questions about opening times, ticket prices and parking. Chatbots struggle with complex questions, and, for them to be effective a user needs to ask short, direct, factual questions. Chatbots can provide operational information - for example the Anne Frank House museum uses a chatbot to answer common visitor questions about visiting, but they can also be creative, for example the Field Museum created a chatbot with a sassy personality for the Maximo, their newly installed T-Rex exhibit.

**Deep learning**

Deep Learning is a subset of machine learning algorithms based on neural networks that use numerous layers, with each layer providing an interpretation of the data it feeds on. The multiple layers are used to progressively extract higher level features from the input data. To give an example from image processing, lower layers may be responsible for detecting edges, while higher layers determine concepts more understandable to a human such as faces, letters or digits. In recent years, deep learning has gained popularity given the huge amounts of data available online from social media, digitalisation efforts and online browsing as well as the availability of increased computation power through GPUs. An example application in a museum context is the use of deep neural networks for indexing the 800 million digital assets at the World Holocaust Remembrance Center in Jerusalem, with the aim of categorising its digital history for researchers and reaching a younger generation.

**GAN (Generative Adversarial Networks)**

A generative adversarial network consists of two neural networks: a generator and a discriminator. A generator creates images based on a dataset and a discriminator determines whether the generated image is real (i.e. it exists in the original dataset) or fake (i.e. generated). The interplay between the two networks enables the generator to create increasingly high-quality images that fool the discriminator. Most systems commonly used nowadays to generate images are a type of GAN. Examples of GAN-based projects includes Gen Studio, a collaboration between MIT, Microsoft and The Met. This project consists of images created using a GAN trained on artworks from The Met's Open Access collection. The generated images enable you to explore and visualise possible artworks between selected pieces from the collections. For example,

you can see what an object between a vase and a goblet could look like.

**Machine Vision**

Machine vision refers to technologies that extract insight from visual input such as images and videos. It looks at individual pixels and the features that are derived from them, seeking patterns in their variations. They include object and facial recognition.

These techniques can be used to find similarities between works across museum collections – examples range from Google's X Degrees of Separation, a project that links two objects through a series of other artworks, to Cooper Hewitt, Smithsonian Design Museum's website, where visitors can explore collections by colour, to Tate's IK Prize Winner 2016 Recognition, a project that matches contemporary photojournalism to art from the Tate's collection. Moreover, it could be used to analyse visitor responses to an exhibition by using facial recognition to analyse the gallery video feed.

**Machine learning**

Machine Learning refers to algorithms that learn to generalise from data, observations and interactions with the world, all without being explicitly programmed. This then allows the algorithms to make a prediction about something in the world, or to generate new, data based on what they have seen. Machine learning is frequently used as an umbrella term to describe a variety of algorithms including neural networks and deep learning. In a museum context, it is frequently applied together or as part of machine vision or natural language processing techniques. at National Norwegian Museum is an example of this. Here, machine learning technologies were applied to museum collections in order to give visitors easier access through better metadata and explorative interfaces. Generative machine learning technologies can be

used for interactive installations such as the Dali Lives project from the Dali Museum in Florida, where visitors are greeted by a deepfake (i.e. AI-generated lookalike) of Salvador Dali and can interact and engage with him on various screens throughout their visit.

#### **Natural language processing**

Natural language processing (NLP) deals with the interaction between computers and human (natural languages). The main objectives are to read, decipher, understand and generate human languages. Nowadays, most NLP techniques rely on machine learning. Applications of NLP include categorising content, analysing sentiments, translation, converting voice into written text and vice versa. In museum fields, NLP can be used to analyse posts from social media or ratings from tourist websites. An example is the inclusion of two virtual educators, Ada and Grace, at the Museum of Science in Boston, who answered visitor questions, suggested exhibits and explained the technology that made them work – including natural language processing.

#### **Neural networks**

Neural networks refer to a type of machine learning algorithm loosely inspired by how neural networks work in the human brain, particularly in terms of processing data and recognising patterns. Neural networks are made up of individual units connected via weights, which are then adjusted as the network is trained. The terms neural networks and deep learning are frequently used interchangeably nowadays, although there are some differences, the main one being the increased number of layers between input and output (hence the “deep”). Neural networks underpin a variety of applications in a museum context, such as being used to generate romantic landscapes in the National Norwegian Museum.

#### **Predictive analytics**

Predictive analytics is a branch of data analytics used to make predictions about unknown future events based on historical data. Predictive analytics uses a variety of techniques from data mining, modelling, statistics and machine learning to generate future insights based on data analysis. From a dataset of museum visitors, predictive analytics systems can estimate visitor numbers for an exhibition on a particular future date or assess the likelihood of membership renewal for certain customer groups. For example, National Museum of African American History and Culture used predictive analytics to research attrition, using data collected from e-tickets to predict demand and piloting Walk-Up Wednesdays to test no-pass entry.

#### **Robots**

Robots are machines that conduct mechanical, routine tasks automatically. Different types of robots are applied in industry, for grasping and moving objects in preparation for delivery for example. In a museum context, we normally deal with humanoid robots, which resemble human beings and are able to replicate certain functions and movements. Paris’ Musée du quai Branly incorporated Berenson, a robotic art critic made to record people’s reactions to artworks and then develop its own taste. The Smithsonian included the humanoid robot Pepper in the National Museum of African American History and Culture, where it is designed to deal with visitor queries and to tell stories using gesture, voice and an interactive touch screen. Meanwhile, the Van Abbemuseum offers a robot for anyone who cannot visit because of physical disability. These visitors can experience the museum from their own home by controlling the robot and guiding it through the museum themselves.

#### **Supervised learning**

Supervised learning is a type of machine learning that learns patterns

entirely from a training dataset, where the data is labelled correctly with the right answer. Based on these patterns, it can predict answers in new data sets by reviewing them. For supervised learning, large labelled datasets are crucial to enable them to effectively generate output data. Incorrect or noisy data labels will reduce the effectiveness of the model. In a museum context, applications of supervised learning include predicting exhibition attendance or automating outreach for donors who may not be planning to renew.

#### **Training Dataset**

Datasets are one of the key pillars of machine learning. In supervised learning, a training dataset is a set of examples used to shape the model to ensure that it fits the data and is able to predict future outcomes correctly. The training dataset consists of pairs of input-output examples (e.g. a drawing of a cat as input and a photograph of a cat as output), which teach the model how to map the inputs to correct outcomes. Given its importance in fitting a machine learning model, it is crucial to have training datasets which are as representative as possible for the future application of the model, as any incomplete or wrongly labelled data will be amplified further down the line as the trained model is applied on unseen data. To give an example in a museum context, if we are looking to make accurate predictions of cafeteria usage, we would need to make sure that the system is trained on multi-seasonal data. If cafeteria usage is highly seasonal and we only trained the system on the last two months, then it will only know about the current season and will provide less accurate predictions as the seasons change.

#### **Unsupervised learning**

Unsupervised learning is a type of machine/deep learning that finds structure where none is defined. It examines data and identifies patterns within it without guidance. It can be applied to find clusters of similar

data, find anomalous data points that look different from everything else. For example in a museum context, unsupervised learning could be used to analyse a dataset of museum visitors and identify clusters of weekends with high visitation (e.g. because of school holidays or certain exhibitions).

#### **Sentiment Analysis**

Sentiment analysis is the contextual mining of text which identifies, extracts, quantifies and studies subjective information and affective states in source material. It can be used to determine the overall attitude of a group – positive or negative – towards a product, organisation or topic. For example, this can help museums understand the social sentiment around an exhibition or artwork from online conversations on social media. The British Museum applied sentiment analysis to two years of TripAdvisor reviews to gain insights from visitor reviews on how visitors experienced the various aspects of a museum eg. exhibition, tours, facilities.

#### **Object recognition**

Object recognition is a general term to describe a set of computer vision techniques for identifying objects in images or videos. These techniques are used for deciding how to classify objects in an image, for identifying the locations of objects within an image or for both tasks. Object recognition includes a variety of possible applications in the museum field, from uses in research and collection management to identification of artworks and visitor engagement through interactive apps. An example of this is the Headhunt! App from the National Portrait Gallery in Australia, where kids can take pictures of the portrait artworks with an iPad and then access interactive learning experiences. Another example is Google Arts & Culture app Art Selfie, which asked users to take a selfie and then, using facial recognition, found the closest matching portrait artwork.

## PROJECT LINKS

### Gen Studio

<https://gen.studio/>

### Google's X Degrees of Separation:

<https://artsexperiments.withgoogle.com/xddegrees/>

### Cooper Hewitt, Smithsonian

#### Design Museum:

<https://collection.cooperhewitt.org/>

### Tate's IK Prize Winner 2016 Recognition:

<https://www.tate.org.uk/whats-on/tate-britain/exhibition/ik-prize-2016-recognition>

### Anne Frank House

<https://www.annefrank.org/en/about-us/news-and-press/news/2017/3/21/anne-frank-house-launches-bot-messenger/>

### Field Museum

<https://www.fieldmuseum.org/exhibitions/maximo-titanosaur>

### National Museum of African American History and Culture

[https://www.slideshare.net/MuseWeb/mw18-presentation-big-data-analytics-in-museum-operations \(p11-17\)](https://www.slideshare.net/MuseWeb/mw18-presentation-big-data-analytics-in-museum-operations (p11-17))

### Musée du quai Branly

<https://www.widewalls.ch/berenson-the-robot-vidal-gaussier/>

### The Smithsonian

<https://www.si.edu/visit/pepper>

### Van AbbeMuseum

<https://vanabbemuseum.nl/en/mediation/inclusion/museum-visit-with-robot/>

### National Portrait Gallery, Australia

<https://catchoom.com/case-studies/headhunt-app-turns-a-museum-visit-into-an-interactive-experience-with-image-recognition/?cn-reloaded=1>

### The British Museum

<https://medium.com/mcnx-london/invisible-insights-learning-from-trip-advisor-reviews-b5c825fa4409>

### ImageNet Roulette

<https://www.excavating.ai/>

### Google Arts & Culture, Art Selfie:

<https://artsandculture.google.com/camera/selfie>

### Dali museum

<https://thedali.org/exhibit/dali-lives/>

### Principal Components

<https://bengler.no/principalcomponents>

### World Holocaust Remembrance Center:

<https://blogs.nvidia.com/blog/2019/05/06/yad-vashem-holocaust-museum-ai-dgx-1/>

### Museum of Science:

<http://ict.usc.edu/prototypes/museum-guides/>

All project weblinks active when accessed January 2020

## ACKNOWLEDGEMENTS

The content for this toolkit was developed through a series of workshops in London and New York that were held in summer 2019. We would like to thank workshop participants for their insights, critiques, curiosity and generosity.

### Network Research Assistants

Dimitra Gkitsa, Goldsmiths, University of London  
Seth Crider, School of Information, Pratt Institute

### Core Network Members

Andrew Lih, Wikimedia Strategist, The Metropolitan Museum of Art  
Ariana French, Director of Digital Technology, American Museum of Natural History  
Carolyn Royston, Chief Experience Officer, Cooper Hewitt, Smithsonian Design Museum  
Casey Scott-Songin, Senior Manager: Data & Insight, The National Gallery, London  
Dan Brennan, Museum Application Developer, Princeton University Art Museum  
Dr Juhee Park, Data Research Fellow, Victoria and Albert Museum Research Institute (VARI)  
Dr Mia Ridge, Digital Curator for Western Heritage Collections, The British Library  
Harrison Pim, Data Scientist, Wellcome Collection  
Jamie Unwin, Collections Technical Architect, Science Museum Group  
Jennie Choi, General Manager of Collection Information, The Metropolitan Museum of Art  
John Stack, Digital Director, Science Museum Group  
Lawrence Chiles, Head of Digital Services, The National Gallery, London  
Rachel Ginsberg, Cooper Hewitt, Smithsonian Design Museum

### London Participants

Ben Vickers, Chief Technology Officer, Serpentine Galleries  
Dr Fiona Johnstone, Research Associate, Centre for Interdisciplinary Methodologies, Warwick University, People Like You  
Dr Giles Bergel, Digital Humanities Research Fellow, Seebibyte, Faculty of Engineering, University of Oxford  
Dr Sophie Frost, Research Assistant, One by One, University of Leicester  
Hannah Barton, Digital Project Manager, Tate  
Joe Padfield, Conservation Scientist, The National Gallery, London  
John Davies, Economic Research Fellow, Creative Economy and Data Analytics, Nesta  
Lisa Ollerhead, Head of Museums Policy, Department of Digital, Culture, Media & Sport  
Meriel Royal, User Experience Researcher, The National Gallery, London

Natalie Kane, Curator of Digital Design, Victoria & Albert Museum  
Nicolas Malevé, PhD Researcher, Centre for the Study of the Networked Image, London South Bank University  
Philo Van Kemenade, Co-founder and Head Curator, Sensorium Festival  
Professor Victoria Alexander, Institute for Creative and Cultural Entrepreneurship, Goldsmiths, University of London  
Rachel Coldicutt, CEO, Doteveryone  
Tom Cunningham, Data Analyst, The National Gallery, London  
Tonya Nelson, Director of Arts Technology and Innovation, Arts Council England  
Victoria Ivanova, PhD Researcher, Centre for the Study of the Networked Image, London South Bank University  
Vishal Kumar, Futurecity Associate, Spatial Data Science and Visualisation, Centre for Advanced Spatial Analysis The Bartlett, University College London

### New York Participants

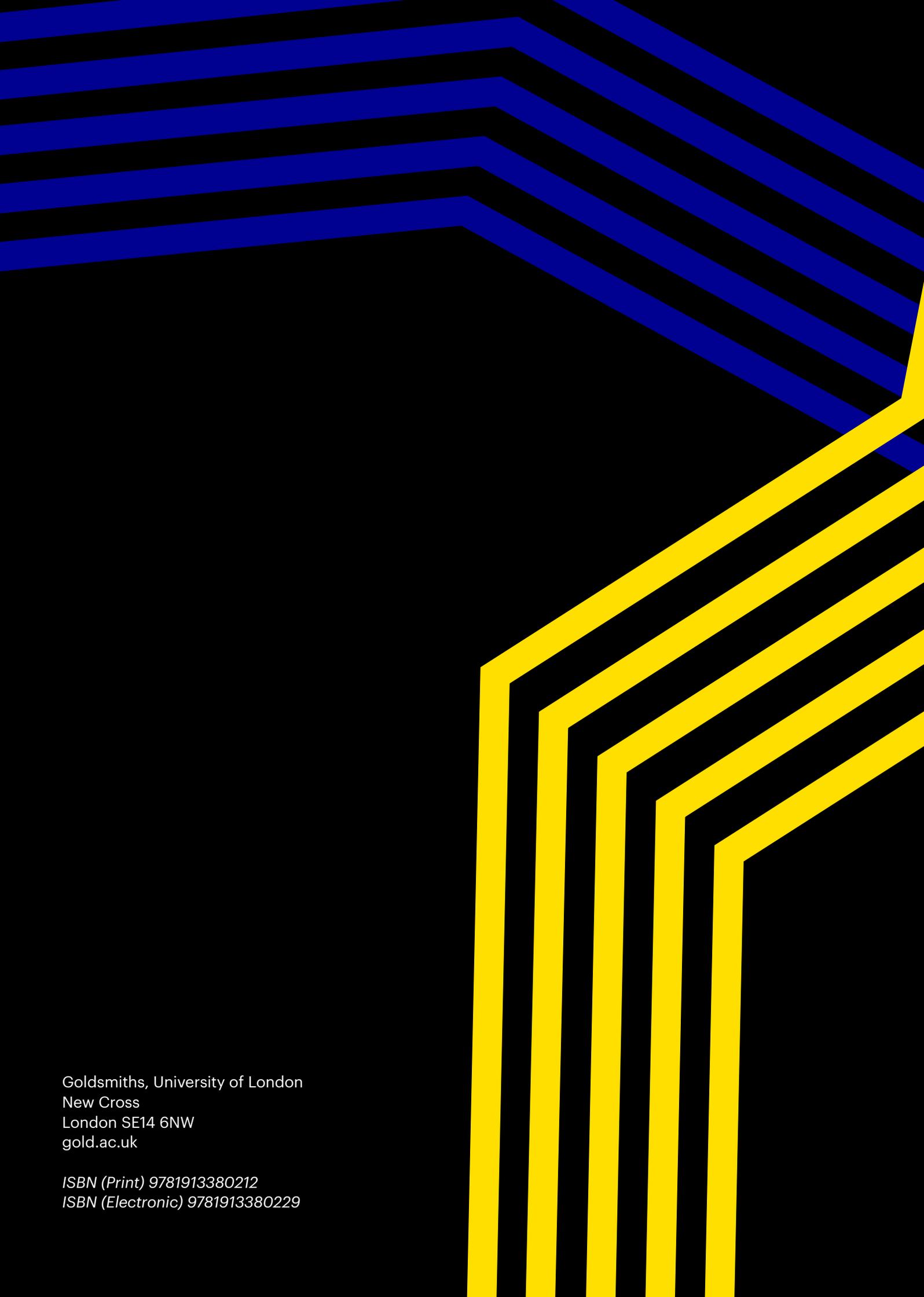
Achim Koh, Visiting Assistant Professor, Pratt Institute  
Adam Quinn, Digital Product Manager, Cooper Hewitt, Smithsonian Design Museum  
Dr Anthony Cocciolo, Dean, School of Information, Pratt Institute  
Dr Chris Sula, Associate Professor, Pratt Institute  
Dr Craig MacDonald, Director, Center for Digital Experiences, Associate Professor, Pratt Institute  
Effie Kapsalis, Senior Digital Programme Officer, American Women's History Initiative, Smithsonian Institute  
Jeff Steward, Director of Digital Infrastructure and Emerging Technology, Harvard Art Museums  
Kang-Ting Peng, Senior Engineer, Cooper Hewitt, Smithsonian Design Museum  
Lawrence Swiader, Director of Digital Strategy, American Battlefield Trust  
Matthew Cock, Chief Executive, Vocal Eyes  
Shannon Darrough, Director, Digital Media, MoMA  
Spencer Kiser, Lead Developer, The Metropolitan Museum of Art

### Public event contributors

Andrea Lipps, Associate Curator of Contemporary Design, Cooper Hewitt, Smithsonian Design Museum  
Dr Oliver Fletcher Vane, Living With Machines, British Library  
Dr Sophie Frost, Executive Director, Furtherfield  
Irina Papadimitriou, Creative Director, Future Everything  
Karen Palmer, Storyteller from the Future  
Laren Vargas, Research Assistant, One by One, University of Leicester

# NOTES



The image features a black background with abstract, geometric line art. In the upper left, several parallel blue lines form a series of nested, slightly irregular shapes that recede into the distance. In the lower right, a series of parallel yellow lines form a similar pattern, appearing to rise from the bottom edge. The lines are thick and have sharp, angular turns, creating a sense of depth and movement.

Goldsmiths, University of London  
New Cross  
London SE14 6NW  
[gold.ac.uk](http://gold.ac.uk)

*ISBN (Print) 9781913380212*

*ISBN (Electronic) 9781913380229*