Ceci n'est pas une Artificial Intelligence: A qualitative exploration of representation of gender and other concepts in Generative art and the wider media

Matteo Di Maio, Cambridge High School

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Abstract: Androids, as we all know, dream of electric sheep. (Generative art Convolutional Neural Networks running the latest semantic captioning weights, do, at least). But what happens when you ask artificial brains like these to imagine and draw abstract, conceptual representations of constructs like gender or sexuality? In this paper, I propose an interesting new angle to gender representation studies: how 'artificial brains' trained in the skills of semantic image association on large web-scraped databases of art and images choose to synthesize and represent gender concepts like dress, colour and body shape. I first analyse some typical gender representations as seen in the media (stock photos, magazine covers, etc), then apply that lens of common attributes, biases, roles and narratives to abstractions generated by BigGAN and VQ-GAN generative art models, utilizing OpenAI's CLIP captioning model for natural language association. There is already a substantial literature exploring the ethical conundrums of AI; while the likes of Steed and Caliskan, 2021 have developed quantitative models to analyse racial, gender and intersectional biases in state of the art image-identification models pretrained on standard databases like ImageNet. My study instead takes a qualitative approach: I analyse the apparent stereotypes present in individual pieces of original generative art. I then comment on how these new artworks offer insight into the societal impact of traditional media representations of gender, as well as the potential issues that arise when biases and representation norms filter through to new media synthesis technologies.

Keywords: gender studies, artificial intelligence, artificial representations, generative art, CLIP

Introduction

Industry-standard "image and caption" datasets used to train the latest Convolutional Neural Networks—such as imagenet_1024, image_net16384, coco, wikiart_1024, wikiart_16384, faceshq, and sflckr—contain a wide array of pictures and representations scraped from the web and classified by humans, often by workers at Amazon's Mechanical Turk. (*Untold History of AI*, 2019). Such datasets are used to train A.I. adept at classifying and categorising images (to improve search engines, for example). An emergingly capable application of A.I. trained on these datasets, however, is image generation—fed a text prompt, a neural network will attempt to construct a visual representation, either abstract or literal. OpenAI's DAL-E leads the field in this area (Ramesh et al., 2021). Ad-hoc hacker attempts at recreating the promise of systems like DAL-E include the Big Sleep, which blends existing image generation networks like Big-GAN or VQ-GAN with OpenAI's open-sourced CLIP CNN, which excels at deciding which images best represent a given caption/text prompt (Radford et al., 2021). Together, this assortment of new technologies has wide implications: from a vibrant new generative art scene, to the increasingly difficult process of fact-checking images. Before we dive into representations through these new mediums, however, it's important to address the nature of gender representation in older, traditional mediums. For it is these old mediums—stock photography, advertising, magazine photography—that populate the datasets generative A.I.s are trained on. The biases and stereotypes of the old thus pervade the new. I have chosen three instances of traditional media to analyse: stills from Arianna Grande's music video 'Dangerous Women'; "Woman Wearing Pink Collard Half-sleeved Top', one of the top hits for the search term "woman" on the stock photo site *Pexels.com*, and the cover of the April 2018 edition of American *Men's Health.*

Figure 1

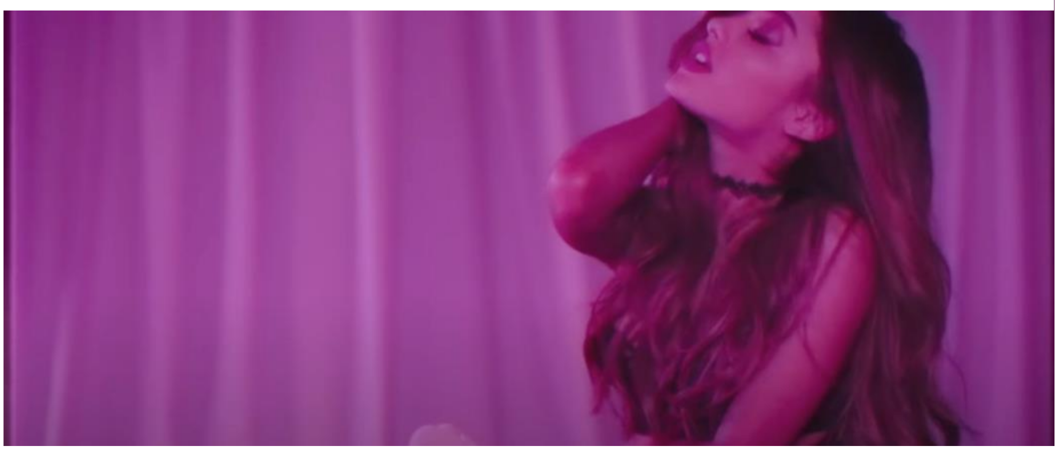

Figure 2

Gender representation in traditional media

A fundamental topic in gender studies is the social construction of semiotic signifiers for gender, particularly surrounding colour. Both my chosen stock image and the music video *Dangerous Women* participate in building an association between the colours pink/purple and feminine gender aspects. Most multi-modal treatments of colour stress that a simple semiotic equation of X colour = social-group Y is flawed; additional aspects like hue, brightness, saturation and matt are important in analysing the nature of a medium's colour signification. In the case of *Dangerous Woman,* both Grande and the plain cloth background behind her are frequently lit in a deep, pink-purple hue; likewise, the saturation of the image is reduced to create a high levels of contrast, with areas of extremely saturated colour. (See Fig. 1 & 2.) I'd argue that this representation of femininity can largely be considered 'post-feminist.' As noted by Koller, 2008: "[In post-feminist subcultures] There seems to be a tendency to reclaim pink and redefine it as the colour of women who regard themselves as having achieved equality in social and economic terms and are therefore able to embrace pink as a marker of their femininity." A multi-modal analysis determines, then, that different shades of the characteristic colour pink represent different aspects of its social association. In Grande's case, the deeper hues of the purple/pink lighting convey a sense of "girl power" in line with the post-feminist reading. As Koller, 2008 goes on to say: "There are very different pinks: powdery baby pink; and deep, luscious or shocking pink. I associate the first with girlie-baby cuteness and the second with feisty, lively girl-power."

This reading is likely, especially given Grande's associations with the feminist movement (other titles include "God is a Woman", for example), and the specific

Figure 3

messaging of *Dangerous Woman.* The opening lyrics describe a familiarly third-wave mode of feminism, in which the idea of forceable social-equity is embraced:

> Don't need permission / Made my decision to test my limits / 'Cause it's my business, God as my witness / Start what I finished / Don't need no hold up / Taking control of this kind of moment /

The pink in Grande's *Dangerous Women,* besides signifying intertextual solidarity with 'girl power' uses of the colour pink, has a more specific goal of creating coherency within Grande's personal brand. The deep pink shade employed in *Dangerous Women* is also seen in other music videos by the same artist: *7 Rings* and *Into You. (*See Figs. 4 & 5.) In the eyes of Grande's fans, pink becomes not only a gender-signifier but also a *brand* signifier. This interpretation feeds into critical narratives of "girl power" as an overly consumerist idea—public figures like Grande with products and merchandise to sell benefit from the association of colour with a social justice message. Another illustration: Barbie doll's recent push to increase their representation of body shapes and colours nonetheless retains the colour pink. This is the reason, for example, that McClure, 2004 warns against celebrating explicitly capitalist notions of 'girl power' as empowering to women: "An ideology based on consumerism can never be a revolutionary social movement. The fact that it appears to be a revolutionary movement is a dangerous lie that not only marketers sell to us but that we often happily sell to ourselves."

No such reclamation of pink can be seen in 'Woman Wearing Pink Collard Half-sleeved Top', my chosen stock image. (See Fig. 3) The woman can be seen in a light pink top, centred in front of a more saturated pink backdrop. Here, the colour pink is part of a more linear semiotic language; where pink operates as both a marker of social identity, and a denotation of femininity. The lighter shade of the woman's top separates her from the darker background. But the lighter shade also triggers a different cognitive association to the darker purple of Grande's video—it suggests refinement, calmness, gentleness; again, aspects of a different kind of femininity to post-feminist 'loudness'.

But the nature of pink itself—it tends to be a lighter colour in general—may clue us on to several of the ways media representations of gender build associations between concepts like "feminine" and psycho-social traits like "gentle", and "poised." For humans have two separate strains of subjective readings of colour—one as a signifier of gender (which

Figure 4

Figure 5

is perhaps more recent, only arising in the current boy=blue, girl=pink form in the post-WWI West), and then as a signifier of emotional characteristics. Pink could, thus, be the ‘glue’ that sticks "female" to associated cliches like "gentle"…

Finally, the gendered semiotic language cultured by popular media like Grande's music video or stock photos has the effect of forcing an arbitrary, binary taxonomy upon gender itself. Stock photos like Fig. 3 build a binary of gender representation culturally; they also enable physical segregation of genders from an early age through coloured clothes, toys and media. When popular mediums associate body shapes and forms with one colour or the other, we grow to understand gender and sex within terms of “blue” and “pink”, which doesn’t leave much room for nuance or gender-diverse expression. And, despite the progressive tendencies of modern parents, this can be a self-perpetuating system: “For parents, it can be difficult to balance political awareness with the wish not to expose their children to peer group ridicule through colour choice.”(Koller, 2008).

Artz & Venkatesh, 1991, note that critical analyses of gender representation tend to

Figure 6

overlook the media’s portrayal of masculinity:

> A related criticism involves the discipline's preoccupation with the representation of women and subsequent lack of focus on the representation of men. This

> exclusion of male representation is an obvious illustration of how gender is more comprehensive than its construction in this research stream. A final criticism is that the research has tended to describe sex-role portrayal but has not fully examined the persuasive implications of gender representation.

This may be true; however, all three of my popular media representations, including the April 2018 cover of Men's Health, share a common thread of representing only an idealistic, and often unattainable standard for physical body condition. Both the male figure on the cover of Men's Health (Fig. 6) and the female figure in the stock photo (Fig. 3) present, in place of the concepts "healthy male" and "stock female", blemish or pore-free bodies. Both figures are thin, young, white and conditioned. And yet, in the context of the Men's health cover specifically, they are positioned as easily attainable. "Hack your fat-loss genes," "Forge your broader shoulders," and "Sculpt a six-pack" scream the captions surrounding the central figure, a model. "Fit at 42", reminds another caption.

A key motif among representations of men in the context of health or fitness is bulging muscle. On the April 2018 cover, this idealisation of muscle is the perfect partner to voracious consumerism; simply try "6 microwave MUSCLE meals," Men's Health suggests. The figure on the front, of course, is not an accurate representation of a fit or normal human being, but instead a social construction of a fit and normal human being. (To ancient humans, bulky six-packs would have been a huge adaptive disadvantage, requiring far more energy to upkeep than they would have brought in (Wiener-Bronner, 2014)). And the woman in stock photo? She too projects an ideal form; thin, with rounded, blemish-less features. A key point to notice when examining these popular media constructions of gender is who *is* being represented, and who *isn't*, especially within the context they appear in. Men's Health is about men, but depicts only a certain kind of man. Fig. 3 is a bog-standard stock photo for the query 'woman', yet it depicts only a certain kind of (white, thin, western) woman.

How, broadly, should we understand these images? Hyper-reality may offer an answer. As the French philosopher and media theorist Jean Baudrillard hypothesised in his Simulacra and Simulation, the three threads of mass media, late capitalism and postmodernity have placed human reality (again, at least in the West) within a kind of 'Simulacra'—a reality constructed entirely of representations of concepts, and yet where the distinction between reality and representation has been lost. (Rivkin & Ryan, 2004) Urbanism removed people from the physical realities of rural life; *sub*-urbanism isolated the bourgeois from other classes, television isolated our minds from actual social relationships. In the Simulacra, the inability of man to differentiate actual "men" from the "hyper-real" men of the popular media is psychosocially damaging, and can thus explain the overarching malaise felt by postmodern society. This lens of hyper-reality and its detriments can thus be applied to understand the impacts of all three representations. Given that they only depict a certain, air-brushed, 'perfect' human form, they enable the loss of perspective among media consumers living in the Simulacra; consumers compare their inevitably blemished bodies to the hyper-real representations, and come out feeling short-changed. There is some empirical evidence of this. As per Field et al., 2005, boys who read men's, fashion, or health/fitness magazines and girls who were trying to look like women in the media were "significantly more likely than their peers to use products to improve appearance or strength." More broadly, media exposure to unrealistically thin images has been shown to lead to dissatisfaction with appearance in both adolescent girls (Levine et al., 1994) and adult women (Wilcox & Laird, 2000). In one study, despite the fact that 65.1% of the men in the sample were within their normal weight for height range (BMI), 80.9% desired to be a weight different than their own. Crucially, more time spent skimming male-orientated magazines was correlated with feelings of dissatisfaction with one's body (Hatoum Moeller & Belle, 2004).

Meta-analysis of gender ideas in AI research

The representations of "men" and "women" discussed in the above section are in many ways anachronisms. Particularly in the last couple of years, popular media has placed an increasing focus on broadening the scope of their representations of gender, race and sexuality. (Conde Nast, 2021) But while society may have moved on from binary gender semiotics, or hyper-real bodies, A.I. is largely stuck learning from outdated datasets. Consider the example of ImageNet, the industry standard, containing over 14 million captioned pictures:

> You open up a database of pictures used to train artificial intelligence systems. At first, things seem straightforward. You're met with thousands of images: apples and oranges, birds, dogs, horses, mountains, clouds, houses, and street signs. But as you probe further into the dataset, people begin to appear: cheerleaders, scuba divers, welders, Boy Scouts, fire walkers, and flower girls. Things get strange: A photograph of a woman smiling in a bikini is labelled a "slattern, slut, slovenly woman, trollop." A young man drinking beer is categorized as an "alcoholic, alky, dipsomaniac, boozer, lush, soaker, souse." A child wearing sunglasses is classified as a "failure, loser, non-starter, unsuccessful person." You're looking at the "person" category in a dataset called ImageNet, one of the most widely used training sets for machine learning.

This paragraph, as per Crawford & Paglen, 2021, is a good introduction to the topic of gender representation in A.I. systems. Predictably, given the nature of ImageNet classifications, machine learning models seem to be able to automatically pick up bias from the way people are stereotypically portrayed in the media. (Note: According to Crawford & Paglen, ImageNet has subsequently pulled much of the "person" category from the web.) Steed & Caliskan, 2021 summarise the findings of their study into intersectional biases in artificial image classification systems as such:

> We find statistically significant racial, gender, and intersectional biases embedded in two state-of-the-art unsupervised image models pre-trained on ImageNet [64], iGPT [14] and SimCLRv2 [13].
>
> We test for 15 previously documented human and machine biases that have been studied for decades and validated in social psychology and conduct the first machine replication of Implicit Association Tests (IATs) with picture stimuli [31].
>
> In 8 tests, our machine results match documented human biases, including 4 of 5 biases also found in large language models. The 7 tests which did not show significant human-like biases are from IATs with only small samples of picture stimuli.

Neural Networks offer an interesting tool with which to empirically test and measure the impacts of given media representations on social biases. Neural Networks have proven to be influenced by the nature of the dataset they are trained on; media theorists could thus alter key datasets—for example only including young females who are dressed in pink—before measuring and quantifying the resultant biases in the trained CNN.

A key quantitative method for critical representation studies is the theory of selection and exclusion. Often, representations can be biased not by the nature of their included content but by what they *do not* represent. In seeming proof of this, the researchers from the above study pinpoint disparities in proportional representation of different people within ImageNet, for example. Thus:

> Under-representation in the training set could explain why, for instance, White people are more associated with pleasantness and Black people with unpleasantness. There is a similar theory in social psychology: most bias takes the form of in- group favouritism, rather than out-group derogation.

Anecdotal evidence indicates more subtle racial and gender biases. In a tweet, Lil Uzi Hurt remarks that: (Solly, n.d.)

> No matter what kind of image I upload, ImageNet Roulette, which categorizes people based on an AI that knows 2500 tags, only sees me as Black, Black African, Negroid or Negro.
>
> Some of the other possible tags, for example, are "Doctor," "Parent" or "Handsome." pic.twitter.com/wkjHPzl3kP

Figure 8

Figure 7

Crawford & Paglen, 2021 highlight another key issue with Computer Vision and image captioning, one familiar to post-structuralist media theorists of more traditional media: "images do not describe themselves." Much as the pipe painted by René Magritte in 1929 in the *Treachery of Images* was, of course, not a pipe but a representation of a pipe, the images in ImageNet are not "cats", per say, but representations of cats. What's more, when CNNs learn to describe and caption images based on training with large human-captioned datasets, they learn, by definition, not what the objects in the images *are*, but what the humans captioning them originally thought they *were*. Even cold, mechanical systems like Computer Vision A.I.s cannot avoid the basic tenet of image representation theory—subjectivity. In summary:

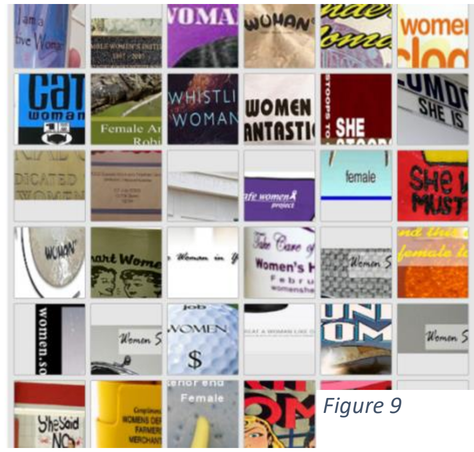

Figure 9

Figure 10

> This is a feature that artists have explored for centuries. Agnes Martin creates a grid-like painting and dubs it "White Flower," Magritte paints a picture of an apple with the words "This is not an apple." We see those images differently when we see how they're labelled. The circuit between image, label, and referent is flexible and can be reconstructed in any number of ways to do different kinds of work. What's more, those circuits can change over time as the cultural context of an image shifts, and can mean different things depending on who looks, and where they are located. Images are open to interpretation and reinterpretation.

The reason Generative art and artificially-conceptualised representations are such a hot topic right now is in large part the huge strides that have recently been made in enabling abstraction and multimodal neurons in CNNs. Researchers have reported the existence of biologically-imitative neurons/nodes in artificial neural networks that 'fire' relative to a specific abstract concept, like a public figure (Goh et al., 2021).

In 2005, a letter published in the journal Nature first identified the phenomenon by which single human neurons would 'fire' or activate when considering single concepts like ‘Jennifer Aniston’ or ‘Michael Jordan’ or the ‘Tower of Piza.’ What was particularly interesting was that these same neurons fired regardless of whether the person in question was shown photographs, images or even written passages referring to the concept in question. This year, a similar process was first noted in OpenAI’s CLIP semantic association program. The researchers write:

> This includes neurons selecting for prominent public figures or fictional characters, such as Lady Gaga or Spiderman. It’s important to note that the vast majority of people these models recognize don’t have a specific neuron, but instead are represented by a combination of neurons. Often, the contributing neurons are conceptually related. For example, we found a Donald Trump neuron which fires (albeit more weakly) for Mike Pence, contributing to representing him. Some of the neurons we found seem strikingly similar to those described in neuroscience.

Semantic association bias is seen once again:

> The abstract features we find in vision models can be seen as a kind of “inverse grounding”: vision taking on more abstract features by connection to language. This includes some of the classic kinds of bias we see in word embeddings, such as a “terrorism”/”Islam” neuron, or an “Immigration”/”Mexico” neuron.

Finally, of interest to my study, given the use of CLIP as part of the VQ-GAN-CLIP generative art model:

> These neurons detect gender. By this, we mean both that it responds to people presenting as this gender, as well as that it responds to concepts associated with that gender and age, as well as facial features like moustaches.

OpenAI’s web program actually allows one to isolate both the ‘female’ and ‘male’ neurons, and the ImageNet frames relative to it. (Unit 2,518 and 320, respectively, to be precise.) (https://microscope.openai.com/models/contrastive_4x/image_block_4_5_Add_6_0/2518.) The web program provides an artificial, optimized image that maximizes activations of the female neuron. (See Fig. 7) This image is especially interesting, as we can see common semiotic associations that clearly maximise the Neural Network’s idea of femininity; the traditional female ♀ glyph, several shades of pink, the word “women” and the contour of an eyebrow. Looking more closely at the ImageNet images that also activate the ‘female’ neuron, we see again the common pink colour theme, plenty of typographic example of “girl,” “female” and “woman,” but also phrases like: “OMFG SHE’S HOT!”, ‘Girl Power’ and several 50s-style cartoons depicting housewives. (See Fig. 8)

The ‘male’ neuron tends to fire most frequently when fed images of spiderman and superhero comics, images of Heineken beer, and images with the word ‘hero’. (Fig. 10) This is not to cherry-pick negative or out-dated associations: the ‘female’ neuron, for example, also fired often when fed images of women’s protest marches or pay-equity placards. (Fig. 9) Nonetheless, it doesn’t take genius to see the not necessarily positive trends that might emerge in an A.I. conceptually trained on these kinds of images or human-led classifications.

Generative AI analysis

I fed several CLIP-based generative art CNNs text prompts regarding abstract gender concepts. Training of models and rendering of images was done on Google-provided GPUs through the collab research interface, using open-access code provided by Hillel Wayne and Katherine Crowson. Both code sets (Katherine Crowson’s uses VQ-GAN) are based on the initial CLIP + Big-GAN pairing first discovered by @avadnoun. (*MIT License*, n.d.)

An important thing to note is that, unlike DAL-E, the GAN models used in my study tend towards very abstract, deconstructionist, and frequently surrealist/psychedelic art styles.


Men in music videos


The ideal woman V2


The meaning of masculinity V3


A magazine cover of the ideal man


A magazine cover of the ideal woman


The meaning of masculinity V1


Women in the media


The meaning of femininity V1


The ideal man


The meaning of masculinity V2


The ideal woman V1


What it means to be a man


Women in music videos (green annotations)


A hero saves the day


The meaning of femininity V2


The relationship between women and men

Rationale behind prompts

The textual prompts I fed to the generative art models fall under two main categories.

1. **Questions regarding subjective interpretations of gender concepts.**
   - 'The meaning of masculinity'
   - 'The meaning of femininity' (V 1 and V2)
   - 'The ideal woman' (V1 and V2)
   - 'The ideal man'
   - 'The relationship between men and women'
   - 'True masculinity'

2. **Questions specifically regarding media portrayals**
   - 'Men in music videos'
   - 'Women in music videos'
   - 'Women in the media'
   - 'A hero saves the day'
   - 'A magazine cover of the ideal man'
   - 'A magazine cover of the ideal woman'

The idea behind the first category of images is to test the CNN with subjective concepts that should ideally indicate the ways in which representation of male and female figures in the media construct an idea of gender norms. The second category is targeted at understanding the impact of media representations directly on the AI's thought process, asking it to re-represent gender ideas in reference to common media.

Key trends in representation

- *Skin colour homogeneity*. One of the most obvious trends in form representation in my sample-set of images is skin colour. The A.I. clearly tends towards using Caucasian skin tones. This is particularly apparent in 'The meaning of femininity', 'the ideal woman V1 and V2' and 'the ideal man.' This is a clear demonstration of representation bias in our data sets feeding through to artificially synthesised representations. A human who lives in an isolated, homogenous community will have a very narrow idea of what it means to be female. Likewise, an A.I. trained on an Euro-centric image data base will have a narrow idea of gender and racial variance. 'The meaning of femininity' V1 and V2 both seem to be clear examples of this. Femininity is a nuanced and complicated social construct, but also a diverse physical phenomena. These paintings, however, largely suggest homogeneity of skin colour. In the same fashion, both

'the meaning of masculinity', 'true masculinity' and 'a portrait of the ideal man' exhibit light apparent skin tones, on the muscled details.
- *Consistency of semiotic vocabulary*. This trend was apparent in the female-related prompts, but not the male-related prompts. All images with the keywords 'female' or 'woman' or

'women' or 'femininity' bar two (the ideal woman V2, the relationship between women and men') made heavy use of pink/purple colours. This is consistent with existing semiotic language surrounding gender, as discussed in both the stock image and *Dangerous Women* examples. The specific hues/shades and the apparent form of the colours changes depending of the artwork in question. Shades in the 'meaning of femininity' V1 vary from saturated light-purple to rose pink. Interestingly, both 'A magazine cover of the ideal man' and 'A magazine cover of the ideal woman' contain pink undertones. While the amount and saturation of the pink is far greater in the 'woman' version of this prompt, there are still light shades on the male version. Perhaps the style of magazine that maximises CLIP's 'magazine' activations are the more early to mid-century style versions; often with diluted pastel colours?

- *Aspects of ideal forms*. Something true of both variations of 'the meaning of masculinity', as well as 'true masculinity' is isolated sections of bulging muscle. 'The meaning of masculinity' V1 contains two instances of deconstructionist, hyperrealist muscle, one in the top left quarter of the painting, and one in the bottom right. These muscle bulges were surprisingly consistent across all paintings containing the key word 'masculinity.' 'True masculinity' is largely constructed of four masses of hirsute muscle. 'The meaning of masculinity' V2 again contains muscle-like forms, this time either heavily tanned or tinted red for apparently stylistic reasons. Together, these artworks from Big-GAN and VQ-GAN suggest that:
    - ◊ AI is extremely receptive to idealised depictions of masculinity in the media, which often contain unrealistically muscly men. (As explained in reference to the April 2018 Men's Health magazine cover.)
    - ◊ And/or; ImageNet data sets overwhelmingly include only muscly men
    - ◊ And/or; ImageNet human classifiers only tag the muscly men within their datasets as "masculine" or "masculinity"

  Either way, these three images collectively indict homogenous traditional representations of masculine body forms. We also see other traditionally "masculine" body forms in the AI's representations. The central face in 'A portrait of ideal man', an almost cubist painting, appears to have a thick beard. Similarly, 'the meaning of masculinity' V1 contains an chin-like form in the bottom left quarter, which is also covered in a thick dark beard.
- *Hints of hyper-sexualisation*? Interestingly, and perhaps impressively, the reductive forms in 'women in music videos' appear to conform to typically curved/sensual/sexual body poses. For instance, consider the two forms highlighted in 'Women in music videos'. This is an especially fascinating aspect of A.I. gender representation; the forms are extremely simplistic and stylised, yet still contain a reductive representation of typical body forms/movements in music videos. The A.I. has thus internalised a seemingly complex set of technical codes and conventions regarding gender representation in popular media music videos.
- *Intertextuality*. There are a surprisingly number of intertextual references in my sample set of generative art. 'The relationship between women and men' appears to draw stylistic inspiration from 50s-style comics/advertisements, particularly with the hair styles of both the male and female figures, the lipstick shades and the general colour scheme of dull, earthy tones.

'A hero saves the day'—a prompt I designed to test the A.I.'s internalisation of traditional narratives around masculinity and heroism, appears to reference the colour schemes of both Iron Man and Spider Man comic. (Remember that a large set of the images CLIP's 'male' neuron is maximally activated by contain vintage comics.) Other than the semiotic reference through colour, not much else is clear in 'a hero saves the day.' 'Women in the media' draws together an interesting collection of abstracted symbols. The painting is divided into a large number of 'tiles', each contorted by slotted together. Several of the tiles take the appearance of newspapers, while others appear to be either TVs or producer screens. The vaguely human figures (there are about 12) consist mainly of short blonde hairstyles, red/pink clothes, and White skin tones.

Conclusions and impacts

If this study makes anything clear, it's that the semiotic trends and intersectional biases within traditional media representations of gender certainly filter through to artificial syntheses of these social concepts. Additionally, generative art promises a new field of intersectional representation studies, measuring both the impact of traditional media on the biases of artificial brains, but also the way artificial brains may choose to synthesis human social relationships and concepts, especially as the technology becomes increasingly sophisticated.

The overall trend observed in my sample set of generative images was homogeneity of aspects of representation. For example, the vast majority of generated representations of feminine text prompts utilised a consistently pink/purple colour scheme, in keeping with existing semiotic relationships between gender and colour. Likewise, all variations on the theme of "man" or "masculinity" presented bulging muscular forms; all human forms presented Caucasian skin tones. This has several impacts.

First, it further supports the theory that unsupervised Neural Networks can assimilate intersectional biases through training on semantic image association in popular media. In illustration of this is the lack of diversity within multiple different representations of gender concepts.

It indicates that semiotic relationships—such as feminine=pink—perpetuated by popular media can easily be internalised by artificial media consumers. Pink, as examined in the first section, only recently became societally associated with gender, although some evolutionary cognitive scientists have suggested sex-differentiated perceptions of colour (Frassanito & Pettorini, 2008). That such a recent cultural association

If Neural Networks trained on ImageNet etc continued to have skewed perceptions of concepts like 'what it means to be a man' in line with the hyper-muscular, overwhelmingly white ideal put forward by traditional media, other applications of image-to-text A.I.s should continue to be closely scrutinised. New technologies like A.I. Dungeon, which uses language processing CNNs like GPT-3 and Griffin to write individualised role-playing narratives, should be studied carefully when describing concepts like gender to players.

Further promising analysis within this emerging field of media studies can hope to test ideas of gender representation in more literal systems like DAL-E, which can construct photo-realistic generated images of text-prompts. (*DALL·E*, 2021) It will also be interesting to see the nature of replications of my kind of study into gender representation in generative art.

Ultimately, this paper serves not as an indictment of generative art as a genre; the field shows real creative promise. Instead, it contributes to the growing literature demonstrating the development of spontaneous biases in artificial brains that learn about the world through human media. Like any artistic movement, generative art is about sorting the good from the bad. Generative art also promises to bring new, perhaps more humanities-orientated perspectives to the field of Artificial Intelligence. (Srinivasan & Parikh, 2021) An overly simplistic view of gender biases in A.I. art would risk rejecting the promise of artificial brains themselves. As Charlie Snell at Berkeley university has noted, CNNs are less imitations of human brains than they are whole new kinds of 'alien' brains. This 'alien' conception of reality promises, conversely, a whole new perspective on art, humanity and reality. (*Alien Dreams: An Emerging Art Scene - ML@B Blog*, n.d.)

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