Large image datasets: A pyrrhic win for computer vision?

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Abstract

In this paper we investigate problematic practices and consequences of large scale vision datasets (LSVDs). We examine broad issues such as the question of consent and justice as well as specific concerns such as the inclusion of verifiably pornographic images in datasets. Taking the ImageNet-ILSVRC-2012 dataset as an example, we perform a cross-sectional model-based quantitative census covering factors such as age, gender, NSFW content scoring, class-wise accuracy, human-cardinality-analysis, and the semanticity of the image class information in order to statistically investigate the extent and subtleties of ethical transgressions. We then use the census to help hand-curate a look-up-table of images in the ImageNet-ILSVRC-2012 dataset that fall into the categories of verifiably pornographic: shot in a non-consensual setting (up-skirt), beach voyeuristic, and exposed private parts. We survey the landscape of harm and threats both the society at large and individuals face due to uncritical and ill-considered dataset curation practices. We then propose possible courses of correction and critique their pros and cons. We have duly open-sourced all of the code and the census meta-datasets generated in this endeavor for the computer vision community to build on. By unveiling the severity of the threats, our hope is to motivate the constitution of mandatory Institutional Review Boards (IRB) for large scale dataset curation.

1. Introduction

Born from World War II and the haunting and despicable practices of Nazi era experimentation [3] the *1947 Nuremberg code* [84] and the subsequent *1964 Helsinki declaration* [27], helped to establish the doctrine of **Informed Consent** which builds on the fundamental notions of human dignity and agency to control dissemination of information about oneself. This has shepherded data collection endeavors in the medical and psychological sciences concerning human subjects, including photographic data [7, 55], for the past several decades. A less stringent version of informed consent, *broad consent*, proposed in 45 CFR 46.116(d) of the *Revised Common Rule* [22], has been recently introduced that still affords the basic safeguards towards protecting one's identity in large scale databases. However, in the age of *Big Data*, these safeguards of informed consent, privacy, or agency of the individual have gradually been eroded. Institutions, academia, and industry alike, amass millions of images of people without consent and often for unstated purposes under the guise of anonymization, a claim that is both ephemeral [56, 67] and vacuous [27]. As can be seen in Table 1, several tens of millions of images of people are found in peer-reviewed literature. These images are obtained without consent or awareness of the individuals or IRB approval for collection. In *Section 5-B* of [79], for instance, the authors state "*As many images on the web contain pictures of people, a large fraction (23%) of the 79 million images in our dataset have people in them*". With this background, we now focus on one of the most celebrated and canonical LSVDs: the *ImageNet* dataset.

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1.1. ImageNet: A brief overview

The emergence of the ImageNet dataset [19] is widely considered a pivotal moment [33] in the *Deep Learning revolution* that transformed Computer Vision (CV), and Artificial Intelligence (AI) in general. Prior to ImageNet, computer vision and image processing researchers trained image classification models on small dataset such as CalTech101 (9k images), PASCAL-VOC (30k images), LabelMe (37k images), and the SUN (131k images) dataset (see slide-37 in [50]). ImageNet, with over 14 million images spread across 21,841 synsets, replete with 1,034,908 bounding box annotations, brought in an aspect of scale that was previously missing. A subset of 1.2 million images across 1000 classes was carved out from this dataset to form the ImageNet-1k dataset (popularly called `ILSVRC-2012`) which formed the basis for the *Task-1: classification* challenge in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). This soon became widely touted as the *Computer Vision Olympics*

Dataset	Number of images (in millions)	Number of categories (in thousands)	Number of consensual images
JFT-300M ([39])	300+	18	0
Open Images ([49])	9	20	0
Tiny-Images ([79])	79	76	0
Tencent-ML ([90])	18	11	0
ImageNet-(21K,11k[1],1k) ([69])	(14, 12, 1)	(22, 11, 1)	0
Places ([93])	11	0.4	0

Table 1: Large scale image datasets containing people's images

[86]. The vastness of this dataset allowed a Convolutional Neural Network (CNN) with 60 million parameters [48] trained by the *SuperVision* team from University of Toronto to usher in the rebirth of the CNN-era (see [2]), which is now widely dubbed the *AlexNet moment* in AI.

Although ImageNet was created over a decade ago, it remains one of the most influential and powerful image databases available today. Its power and magnitude is matched by its unprecedented societal impact. Although an *a posteriori* audit might seem redundant a decade after its creation, ImageNet's continued significance and the culture it has fostered for other LSVDs warrants an ongoing critical dialogue. From the questionable ways images were sourced, to troublesome labeling of people in images, to the downstream effects of training AI models using such images, ImageNet and LSVDs in general *constitute a Pyrrhic win* for computer vision. We argue, this win has come at the expense of harm to *minoritized groups* and further aided the gradual erosion of privacy, consent, and agency of both the individual and the collective.

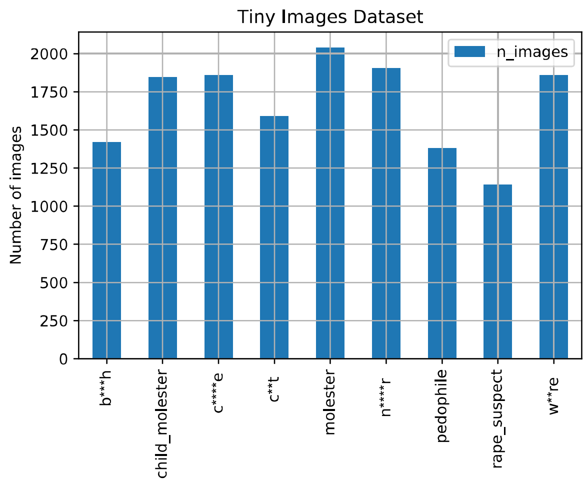
The rest of this paper is structured as follows. In section 2, we cover related work that has explored the ethical dimensions that arise with LSVD. In section 3, we describe the landscape of both the immediate and long term threats individuals and society as a whole encounter due to ill-considered LSVD curation. In Section 4, we propose a set of solutions which might assuage some of the concerns raised in section 3. In Section 5, we present a template quantitative auditing procedure using the ILSVRC2012 dataset as an example and describe the data assets we have curated for the computer vision community to build on. We conclude with broad reflections on LSVDs, society, ethics, and justice.

2. Background and related work

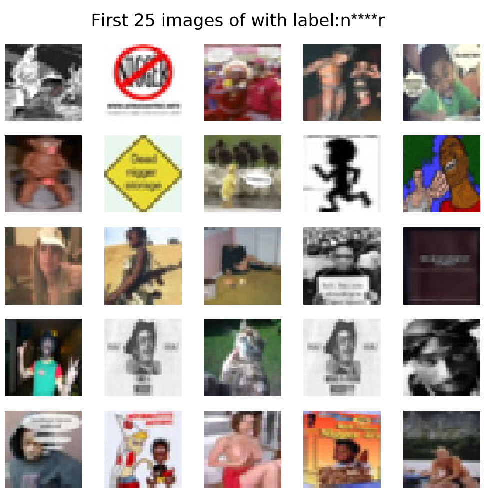
The very declaration of a taxonomy brings some things into existence while rendering others invisible [8]. A gender classification system that conforms to essentialist binaries, for example, operationalizes gender in a cis-centric way resulting in exclusion of non-binary and transgender people [47]. Categories simplify and freeze nuanced and complex narratives, obscuring political and moral reasoning behind a category. Over time, messy and contingent histories hidden behind a category are forgotten and trivialized [75]. With the adoption of taxonomy sources, image datasets inherit seemingly invisible yet profoundly consequential shortcomings. The dataset creation process, its implication for ML systems, and subsequently, the societal impact of these systems has attracted a substantial body of critique. We categorize this body of work into two groups that complement one another. While the first group can be seen as concerned with the broad downstream negative effects, the other concentrates mainly on the dataset creation process itself.

2.1. Broad critiques

The absence of critical engagement with canonical datasets disproportionately negatively impacts women, racial and ethnic minorities, and vulnerable individuals and communities at the margins of society [6]. For example, image search results both exaggerate stereotypes and systematically under-represent women in search results for occupations [46]; object detection systems designed to detect pedestrians display higher error rates towards individuals with dark skin tones [88]; and gender classification systems show disparities in accuracy where lighter-skin males are classified with the highest accuracy while darker-skin females suffer the most misclassification [12]. Gender classification systems that lean on binary and cis-genderist constructs operationalize gender in a trans-exclusive way resulting in tangible harm to trans people [47]. With a persistent trend where minoritized and vulnerable individuals and communities often disproportionately suffer the negative impacts of ML systems, D'Ignazio and Klein have called for a shift in rethinking ethics not just as a fairness metric to mitigate the narrow concept of bias but as practice that results in justice for the most negatively impacted [23]. Similarly, Kasy and Abebe contend that perspectives that acknowledge existing inequality and redistribute power are pertinent as opposed to fairness-based perspectives [45]. Such understanding of *ethics as justice* then requires a focus beyond *bias* and *fairnesss* in LSVDs and calls for bigger questions such as how images are sourced, labelled, and what it means for models to be trained on them. In this regard, through interactive online exhibitions, Crawford and Paglen have unveiled the dark side of LSVDs and the troubling consequences of classifying people as if they are objects [18]. Offensive and derogatory labels that perpetuate historical and current prejudices were assigned to people's actual images. Not only are images that were scraped across the web appropriated as data for computer vision tasks, but also the very act of assigning labels to people based on physical features raises fundamental concerns around reviving long-discredited pseudo-scientific ideologies of physiognomy [91].



(a) Class-wise counts of the offensive classes



(b) Samples from the class labelled `n****r`

Figure 1: Results from the *80 Million Tiny Images* dataset

2.2. Critiques of the curation phase

Within the dataset creation process, *taxonomy sources* pass on their limitations and unquestioned assumptions. The adoption of underlying structures presents a challenge where — without critical examination of the architecture — ethically dubious taxonomies are inherited. This has been one of the main challenges for ImageNet given that the dataset is built on the backbone of WordNet's structure. Acknowledging some of the problems, the authors from the ImageNet team did recently attempt to address [92] the stagnant concept vocabulary of WordNet. They admitted that only 158 out of the 2,832 existing synsets should remain in the person sub-tree[2]. Nonetheless, some serious problems remain untouched. This motivates us to address in greater depth the overbearing presence of the *WordNet effect* on image datasets.

2.3. The WordNet Effect

ImageNet is not the only LSVD that has inherited the shortcomings of the WordNet taxonomy. The *80 million Tiny Images* dataset [79] which grandfathered the CIFAR-10/100 datasets also used the same path. Unlike ImageNet, this dataset has never been audited or scrutinized[3] and some of the sordid results from inclusion of *ethnophaulisms* in its label space are displayed in Figure 1. The figure demonstrates both the number of images in a subset of the *offensive* classes (sub-figure(a)) and the exemplar images (sub-figure(b)) that show the images in the noun-class labelled `n****r`[4], a worrying reminder that a great deal of work remains to be done by the ML community at large. The *labeling and validation* of the curation process also presents ethical challenges. Recent works such as [35] have explored the intentionally hidden labour, which they have termed as *Ghost Work*, behind such tasks. Image labeling and validation requires the use of crowd-sourcing platforms such as MTurk, often contributing to the exploitation of underpaid and undervalued *gig workers*. Within the topic of image labeling but with a different dimension and focus, recent work such as [80] and [5] has revealed the shortcomings of human-annotation procedures used during the ImageNet dataset curation. These shortcomings, the authors point out, include single label per-image procedure that causes problems given that real-world images often contain multiple objects, and inaccuracies due to "overly restrictive label proposals".

3. The threat landscape

In this section, we survey the landscape of harm and threats, both immediate and long term, that emerge with dataset curation practices in the absence of careful ethical

[2] In order to prune all the nodes. They also took into account the *imageability* of the synsets and the skewed representation in the images pertaining to the *Image retrieval* phase

[3] In response to the mainstream media covering a pre-print of this work, we were informed that the curators of the dataset have withdrawn the dataset with a note accessible here: https://groups.csail.mit.edu/vision/TinyImages/

[4] Due to its offensiveness, we have censored this word here, however, it remains uncensored on the website at the time of writing.

considerations and anticipation for negative societal consequences. Our goal here is to bring awareness to the ML and AI community regarding the severity of the threats and to motivate a sense of urgency to act on these. We hope this will result in practices such as the mandatory constitution of IRBs for LSVD curation processes.

The rise of reverse image search engines, loss of privacy, and the blackmailing threat: Reverse image search engines[5] (RISE) that allow face search such as [62] have gotten remarkably and worryingly efficient in the past year. For a small fee, anyone can now use a RISE portal or their API[6] to run an automated procedure and uncover the *real-world* identities of the individuals in a given image. This, we argue, has grave consequences to not just the vulnerable and marginalized sections of the society (such as women discretely employed in sex-work), but also, to the persons in LSVDs. As noted in works such as [51], there's an entire spectrum of image-based sexual abuse that LSVDs such as ImageNet are now unwittingly abetting in a large scale and automated fashion.To further emphasize this specific point, many of the images in classes such as `maillot`, `brassiere`, and `bikini` contain images of beach voyeurism and other non-consensual cases of digital image gathering (covered in detail in Section 5). We were able to (unfortunately) map the victims, most of whom are women, from the ImageNet dataset to *real-world* identities of people, who happened to belong to a myriad of backgrounds including teachers, medical professionals, and academic professors using reverse image search engines such as [62]. Paying heed to the possibility of the *Streisand effect*[7], we made the decision not to divulge any further quantitative or qualitative details on the extent or the location of such images in the dataset besides alerting the curators of the dataset(s) and making a passionate plea to the community not to underestimate the severity of this particular threat vector.

The emergence of even larger and more opaque datasets: The attempt to build computer vision has been gradual and can be traced as far back as 1966 to Papert's *The Summer Vision Project* [59], if not earlier. However, ImageNet, with its vast amounts of data, has not only erected a canonical landmark in the history of AI, it has also paved the way for even bigger, more powerful, and suspiciously opaque datasets. The lack of scrutiny of the ImageNet dataset by the wider computer vision community has only served to embolden institutions, both academic and commercial, to build far bigger datasets without scrutiny (see Table 1). Various highly cited and celebrated papers in recent years [9, 14, 39, 77], for example, have used the *unspoken unicorn* amongst large scale vision datasets, that is, the JFT-300M dataset [?][8]. This dataset is inscrutable and operates in the dark, to the extent that there has not even been official communication as to what *JFT-300M* stands for. All that the ML community knows is it purportedly boasts more than 300M images spread across 18k categories. The open source variant(s) of this, the *Open Images V4-5-6* [49] contains a subset of 30.1M images covering 20k categories (and also has an extension dataset with 478k crowd-sourced images across more than 6000 categories). While parsing through some of the images, we found **verifiably**[9] non-consensual images of children that were siphoned off of *flickr* hinting towards the prevalence of similar issues for JFT-300M from which this was sourced. Besides the other large datasets in Table 1, we have cases such as the *CelebA-HQ* dataset, which is actually a *heavily processed* dataset which grey-box curation process only appears in Appendix-C of [44] (where no clarification is provided on this *"frequency based visual quality metric"* used to sort the images based on *quality*). Benchmarking any downstream algorithm off such an opaque, biased and a (semi-)synthetic dataset will only result in scenarios such as [52], where the authors had to hurriedly incorporate addendums admitting biased results. Hence, it is important to reemphasize that the existence and use of such datasets bears direct and indirect impact on people, given that decision making on social outcomes increasingly leans on ubiquitously integrated AI systems trained and validated on such datasets. Yet, despite such profound consequences, critical questions such as where the data comes from or whether the images were obtained consensually are hardly considered part of the LSVD curation process.

The more nuanced and perhaps indirect impact of ImageNet is the **culture** that it has cultivated within the broader AI community: a culture where the appropriation of images of real people as raw material free for the taking has come be to perceived as *the norm*. Such a norm, and lack of scrutiny, have played a role towards the creation of monstrous and secretive datasets without much resistance, prompting further questions such as *what other secretive datasets currently exist hidden and guarded under the guise of proprietary assets?* Current work that has sprung out of secretive datasets, such as Clearview AI [38] [10], points to a deeply worrying and insidious threat not only to vulnerable groups but also to the very meaning of privacy as we know it [42].

[5]For example, PimEyes: `https://bit.ly/3bSKcZQ`

[6]Please refer to the supplementary material for screenshots

[7]The Streisand effect *"is a social phenomenon that occurs when an attempt to hide, remove, or censor information has the unintended consequence of further publicizing that information, often via the Internet"* [87]

[8]We have decided to purposefully leave the '?' in place and plan to revisit it only after the dataset's creator(s) publish the details of its curation

[9]See `https://bit.ly/2y1sC7i`. We performed verification with the uploader of the image via the Flickr link shared.

[10]Clearview AI is a US based privately owned technology company that provides facial recognition services to various customers including North American law enforcement agencies. With more than 3 billion photos scraped from the web, the company operated in the dark until its services to law enforcement were reported in late 2019

The Creative Commons fallacy: In May 2007 the iconic case of *Chang versus Virgin mobile: The school girl, the billboard, and virgin* [15] unraveled in front of the world, leading to widespread debate on the uneasy relationship between personal privacy, consent, and image copyright, initiating a substantial corpus of academic debate (see [13, 16, 17, 37]). A Creative Commons license addresses only copyright issues – not privacy rights or consent to use images for training. Yet, many of the efforts beyond ImageNet, including the Open Images dataset [49], have been built on top of the *Creative commons* loophole that LSVD curation agencies interpret as a *free for all, consent-included* green flag. This, we argue, is fundamentally fallacious as is evinced in the views presented in [53] by the Creative commons organization that reads: *"CC licenses were designed to address a specific constraint, which they do very well: unlocking restrictive copyright. But copyright is not a good tool to protect individual privacy, to address research ethics in AI development, or to regulate the use of surveillance tools employed online."*. Datasets culpable of this *CC-BY heist* such as *MS-Celeb-1M* and *IBM's Diversity in Faces* have now been deleted in response to the investigations (see [26]) lending further support to the Creative Commons fallacy.

Blood diamond effect in models trained on this dataset: Akin to the *ivory carving-illegal poaching* and *diamond jewelry art-blood diamond* nexuses, we posit that there is a similar moral conundrum at play here that affects all downstream applications entailing models trained using a *tainted* dataset. Often, these transgressions may be rather subtle. In this regard, we pick an exemplar field of application that on the surface appears to be a low risk application area: *Neural generative art*. Neural generative art created using tools such as BigGAN [9] and Art-breeder [73] that in turn use pre-trained deep-learning models trained on ethically dubious datasets, bear the downstream burden[11] of the problematic residues from non-consensual image siphoning. We also note that there is a privacy-leakage facet to this *downstream burden*. In the context of face recognition, works such as [74] have demonstrated that CNNs with high predictive power unwittingly accommodate accurate extraction of subsets of the facial images that they were trained on, thus abetting dataset leakage.

Perpetuation of unjust and harmful stereotypes: Finally, zooming out and taking a broad perspective allows us to see that the very practice of embarking on a classification, taxonomization, and labeling task endows the classifier with the power to decide what is a legitimate, normal, or correct way of being, acting, and behaving in the social world [8]. For any given society, what comes to be perceived as *normal* or *acceptable* is often dictated by dominant ideologies. Systems of classification, which operate within power asymmetrical social hierarchies, necessarily embed and amplify historical and cultural prejudices, injustices, and biases [75]. In western societies, "desirable", "positive", and "normal" characteristics and ways of being are constructed and maintained in a way that aligns with the dominant narrative, giving advantage to those that fit the status quo. Groups and individuals on the margins, on the other hand, are often perceived as the "outlier", "deviant", and "edge-case". Image classification and labelling practices, without the necessary precautions and awareness of these problematic histories, pick up these stereotypes and prejudices and perpetuate them [28, 57, 58]. AI systems trained on such data amplify and normalize these stereotypes, inflicting unprecedented harm on those that are already on the margins of society. While the ImageNet team did initiate strong efforts towards course-correction [92], the Tiny Images dataset still contains harmful slurs and offensive labels. And worse, we remain in the dark regarding the secretive and opaque LSVDs.

[11] Please refer to the supplementary material where we demonstrate one such real-world experiment entailing unethically generated neural art replete with responses obtained from human critiques as to what they felt about the imagery being displayed.

4. Candidate solutions: The path ahead

Decades of work within the fields of Science and Technology Studies (STS) and the Social Sciences show that there is no single straightforward solution to most of the wider social and ethical challenges that we have discussed [4, 23, 76]. These challenges are deeply rooted in social and cultural structures and form part of the fundamental social fabric. Feeding AI systems on the world's beauty, ugliness, and cruelty, but expecting it to reflect only the beauty is a fantasy [4]. These challenges and tensions will exist as long as humanity continues to operate. Knowledge of the past as well as awareness of socially ingrained power asymmetries are critical first steps towards ethics and justice oriented data curation. Given the breadth of the challenges that we have faced, any attempt for a quick fix risks concealing problems and providing a false sense of solution. The idea of a complete removal of biases, for example, not only rests on the misguided assumption that there exists a "bias free" dataset, but also might serve to simply hide bias out of sight [34]. Furthermore, many of the challenges (bias, discrimination, injustice) vary with context, history, and place, and are concepts that continually shift and change constituting a moving target [6]. The pursuit of panacea in this context, therefore, is not only unattainable but also misguided. Having said that, there are remedies that can be applied to overcome the specific harms that we have discussed in this paper, which eventually play constituent roles in improving the wider and deeper social and structural issues in the long run.

Remove, replace, and open strategy: In [92], the authors concluded that within the *person sub-tree* of the ImageNet dataset, 1593 of the 2832 people categories were *potentially*

Dataset audit card - ImageNet

Census audit statistics

- 83436 images with $101070 - 132201$ persons (Models: DEX ([68]), InsightFace ([36]))
- Mean-age (male): 33.24 (Female):25.58 (RetinaFace [21], ArcFace [20])
- Confirmed misogynistic images: 62. Number of classes with infants: 30
- ($\mu_c^{(A)}$ and $\sigma_c^{(A)}$: Mean and standard-deviation of the gender-estimate of images in class c estimated by algorithm (A).)

Metrics: Class-level mean count ($\eta_c^{(A)}$), mean gender skewness ($\xi_c^{(A)}$) and mean-age ($\alpha_c^{(A)}$):

$$\eta_c^{(A)} = \frac{1}{N_c}\sum_{i=1}^{N_c} I[\phi_i], \alpha_c^{(A)} = \frac{1}{N_c}\sum_{i=1}^{N_c} I[\phi_i] a_i^{(A)} \; and$$

$$\xi_c^{(A)} = \frac{1}{N_c}\sum_{i=1}^{N_c} I[\phi_i] \left(\frac{g_i^{(A)} - \mu_c^{(A)}}{\sigma_c^{(A)}}\right)^3$$

$$\phi_i = \begin{cases} 1 & \text{if face present} \\ 0 & \text{otherwise} \end{cases} \text{ in } i^{th} \text{ image.}$$

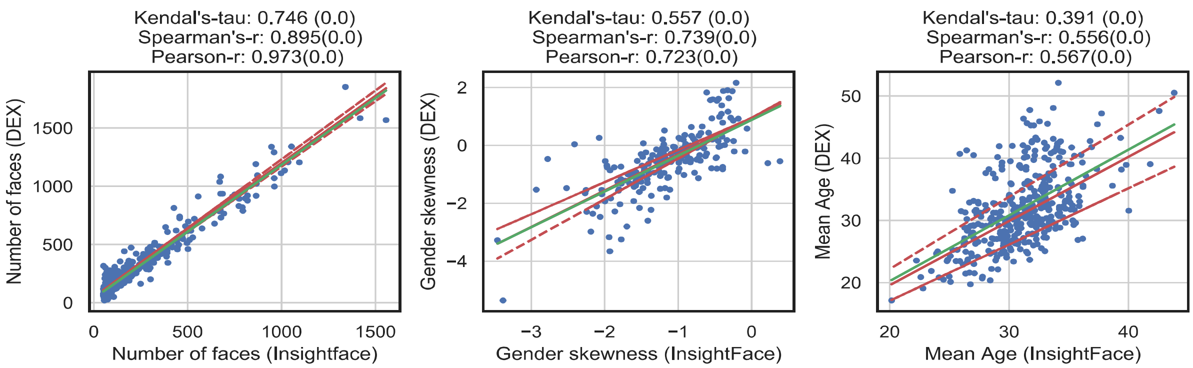


Figure 2: Class-wise cross-categorical scatter-plots across the cardinality, age and gender scores

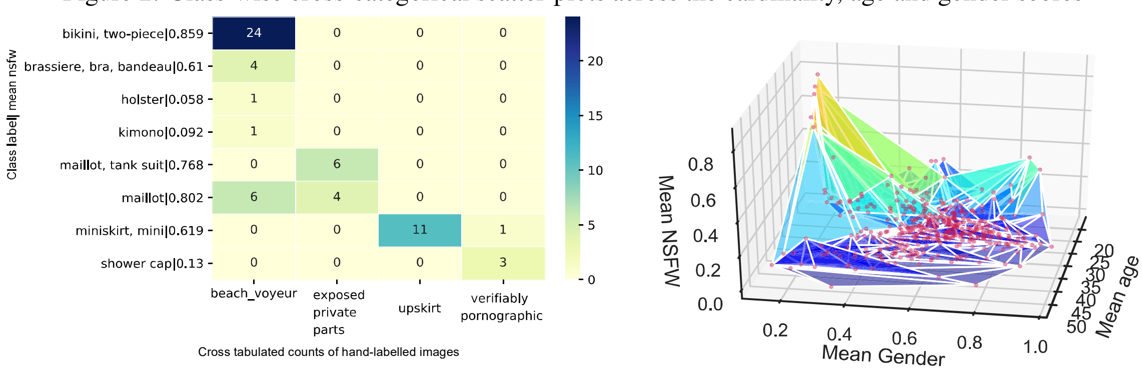


Figure 3: Statistics and locationing of the hand-labelled images

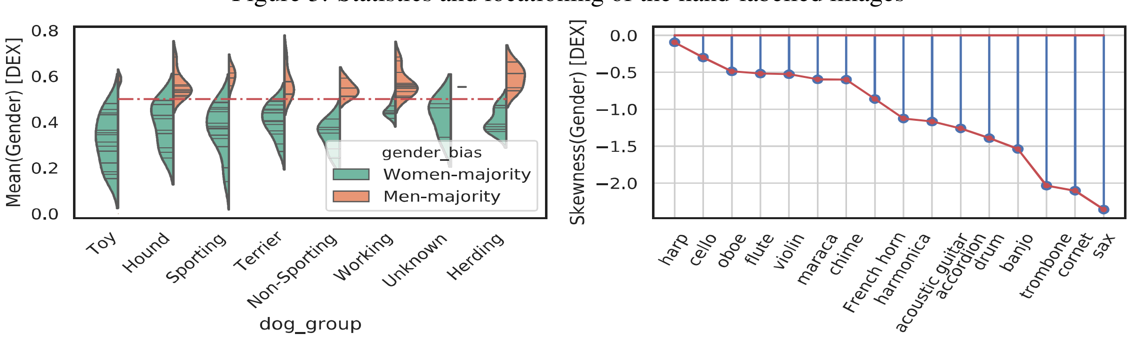


Figure 4: Known *human co-occurrence* based gender-bias analysis

Figure 5: Dataset audit card for the ImageNet dataset

offensive labels and planned to *"remove all of these from ImageNet."*. We strongly advocate a similar path for the offensive noun classes in the Tiny Images dataset that we have identified in this paper[12]. In cases where the image category is retained but the images are not, the option of *2: replacement with consensually shot financially compensated images* arises. It is possible that some of the people in these images might come forward to consent and contribute their images in exchange for fair financial compensation, credit, or out of sheer altruism [10]. We re-emphasize that our consternation focuses on the non-consensual aspect of the images and not on the category-class and the ensuing content of the images in it. This solution, however, brings forth further questions: does this make image datasets accessible only to those who can afford it? Will we end up with pools of images with a predominantly financially disadvantaged participants? Science is self-correcting so long as it is accessible and open to critical engagement and this is what we have done given what we know of these LSVDs. We strongly contend that making them open and accessible is crucial point towards an ethical scientific endeavour.

Differentially private obfuscation of the faces : This path entails harnessing techniques such as DP-Blur [29] with quantifiable privacy guarantees to obfuscate the identity of the humans in the image. The *Inclusive images challenge* [72], for example, already incorporated blurring during dataset curation [43] and addressed the downstream effects surrounding change in predictive power of the models trained on the blurred versions of the dataset curated. We believe that replication of this template that also clearly included avenues for recourse in case of an erroneously non-blurred image being sighted by a researcher will be a step in the right direction for the community at large.

Synthetic-to-real and Dataset distillation: The basic idea here is to utilize (or augment) synthetic images in lieu of real images during model training. Approaches include using hand-drawn sketch images (*ImageNet-Sketch* [82]), using GAN generated images [24] and techniques such as *Dataset distillation* [83],where a dataset or a subset of a dataset is distilled down to a few representative ***synthetic*** samples. This is a nascent field with some promising results emerging in unsupervised domain adaptation across visual domains [60] and universal digit classification [63].

Ethics-reinforced filtering during the curation and IRBs: Some of the specific ethical transgressions that emerged during our longitudinal analysis of ImageNet could have been prevented if there were explicit instructions provided to the *MTurkers* during the dataset curation phase to enable filtering of these images at the source (see Fig.9 in [66] for example. Although it is important to acknowledge that this is not a problem that dataset curators can leave to MTurkers). IRBs that have been *integral to the U.S. system of protection of human research participants* [1] in empirical research, can play an important role towards a more ethical data curation process. While acknowledging the shortcomings of the IRB process, the very practice of going through the IRB-approval undertaking, will inspire *ethics checks* that can then become an integral part of the user-interface deployed during the humans-in-the-loop validation phase for future dataset curation endeavors. IRB processes regarding LSVD curation also help centre important concepts such as ethics, privacy, and autonomy as something that need to be seen as part of the data curation process.

Dataset audit cards: Much along the lines of *model cards* [54] and *datasheet for datasets* [32], we propose dissemination of *dataset audit cards*. This allows LSVD curators to publish the goals, curation procedures, known shortcomings and caveats alongside their dataset dissemination.
In Figure 5, we have curated an example dataset audit card for the ImageNet dataset using the quantitative analyses carried out in Section 5.

5. Quantitative dataset auditing

We performed a cross-categorical quantitative analysis of ImageNet to assess the extent of the ethical transgressions and the feasibility of model-annotation based approaches. This resulted in an *ImageNet census*, entailing both image-level as well as class-level analysis across the 57 different metrics (see supplementary section) covering Count, Age and Gender (CAG), NSFW-scoring, semanticity of class labels and accuracy of classification using pre-trained models. We have distilled the important revelations of this census as a *dataset audit card* presented in Figure 5. This audit also entailed a human-in-the-loop based hybrid-approach. That is, we firstly used the pre-trained-model annotations (along the lines of [25, 92]) to segment the entire dataset into smaller sub-sets and then hand-labelled the smaller subsets to generate two *verified* lists covering 62 misogynistic images and 30 image-classes with co-occurring children. We used the `DEX` [68] and the `InsightFace` [36] pre-trained models[13] to generate the cardinality, gender skewness, and age-distribution results captured in Figure 2. This resulted in discovery of **83,436** images with persons, encompassing **101,070 to 132,201** individuals, thus constituting $8-10\%$ of the dataset. Further, we munged together gender, age,

[12]During the paper review period, the creators of the Tiny Images dataset acknowledged the shortcomings and decided to withdraw the dataset `http://groups.csail.mit.edu/vision/TinyImages/`

[13]While harnessing these pre-trained gender classification models, we would like to **strongly emphasize** that the specific models and the *problems* that they were intended to solve, when taken in isolation, stand on ethically dubious grounds themselves. In this regard, we strongly concur with previous work such as [85] that *gender classification* based on appearance of a person in a digital image is both **scientifically flawed** and is a technology that bears a high risk of systemic abuse.

file_name	shape	file_contents
df_insightface_stats.csv	(1000, 30)	24 classwise statistical parameters obtained by running the InsightFace model ([36]) on the ImageNet dataset
df_audit_age_gender_dex.csv	(1000, 12)	11 classwise (ordered by the wordnet-id) statistical parameters obtained from the json files (of the DEX paper) [68]
df_nsfw.csv	(1000, 5)	The mean and std of the NSFW scores of the train and val images arranged per-class. (Unnamed: 0: WordNetID of the class)
df_acc_classwise_resnet50.csv	(1000, 7)	Classwise accuracy metrics (& the image level preds) obtained by running the ResNet50 model on ImageNet train and Val sets
df_acc_classwise_NasNet_mobile.csv	(1000, 7)	Classwise accuracy metrics (& the image level preds) obtained by running the NasNet model on ImageNet train and Val sets
df_imagenet_names_umap.csv	(1000, 5)	DF with 2D UMAP embeddings of the Glove vectors of the classes of the ImageNet dataset
df_census_imagenet_61.csv	(1000, 61)	The MAIN census dataframe covering class-wise metrics across 61 parameters, all of which are explained in df_census_columns_interpretation.csv
df_census_columns_interpretation.csv	(61, 2)	The interpretations of the 61 metrics of the census dataframe above!
df_hand_survey.csv	(61, 3)	Dataframe contaimning the details of the 61 images unearthed via hand survey (Do not pay heed to 61. it is a mere coincidence)
df_classes_tiny_images_3.csv	(75846, 3)	Dataframe containing the class_ind, class_name (wordnet noun) and n_images
df_dog_analysis.csv	(7, 4)	Dataframe containing breed, gender_ratio and survey result from the paper Breed differences in canine aggression'

Table 2: Meta datasets curated during the audit processes

class semanticity[14] and NSFW content flagging information from the pre-trained `NSFW-MobileNet-v2` model [31] to help perform a guided search of misogynistic consent-violating transgressions. This resulted in discovery of 62 images[15] across four categories: *beach-voyeur-photography, exposed-private-parts, verifiably pornographic and upskirt* in the following classes: *445-Bikini, 638 -maillot, 639-tank suit, 655-miniskirt* and *459-brassiere* (see Figure 3). Lastly, we harnessed literature from areas spanning from dog-ownership bias ([40],[65]) to engendering of musical instruments ([89], [11]) to generate analysis of subtle forms of *human co-occurrence*-based gender bias in Figure 4.
Captured in Table 2 are the details of the *csv* formatted data assets curated for the community to build on. The CAG statistics are covered in df_insightface_stats.csv and df_audit_age_gender_dex.csv. Similarly, we have also curated NSFW scoring (df_nsfw.csv), Accuracy (df_acc_classwise_resnet50/_NasNet_mobile.csv) and Semanticity (df_imagenet_names_umap.csv) datasets as well. df_census_imagenet_61.csv contains the 61 cumulative parameters for each of the 1000 classes (with their column interpretations in df_census_columns_interpretation.csv). We have duly open-sourced these meta-datasets and 14 tutorial-styled Jupyter notebooks (spanning both ImageNet and Tiny-Images datasets) for community access[16].

6. Conclusion and discussion

We have sought to draw the attention of the machine learning community towards the societal and ethical implications of LSVDs, such as the problem of non-consensual images and the oft-hidden implications of categorizing people. ImageNet has been championed as one of the most incredible breakthroughs in computer vision, and AI in general. We indeed celebrate ImageNet's achievement and recognize the creators' efforts to grapple with some ethical questions. Nonetheless, ImageNet as well as other LSVDs remain troublesome. In hindsight, perhaps the ideal time to have raised ethical concerns regarding LSVD curation would have been in 1966 at the birth of *The Summer Vision Project* [59]. The right time after that was when the creators of ImageNet embarked on the project to "map out the entire world of objects". Nonetheless, these are crucial conversations that the computer vision community needs to engage with **now** given the rapid democratization of imaging scraping tools ([70, 71, 81]) and *dataset-zoos* ([41, 64, 78]). The continued silence will only serve to cause more harm than good. In this regard, we have outlined a few solutions, including *audit cards*, that can be considered to alleviate some of the concerns raised. We have also curated meta-datasets and open-sourced the code to carry out quantitative auditing using the ILSVRC2012 dataset as a template. However, we posit that the deeper problems are rooted in the wider structural traditions, incentives, and discourse of a field that treats ethical issues as an afterthought. A field where *in the wild* is often a euphemism for *without consent* and where powerful corporations have mastered *ethics shopping*, *ethics bluewashing*, *ethics lobbying*, *ethics dumping*, and *ethics shirking* [30]. Within such an ingrained tradition, even the most thoughtful scholar can find it challenging to pursue work outside the frame of the ***tradition***. Subsequently, radical ethics that challenge deeply ingrained traditions need to be incentivised and rewarded in order to bring about a shift in culture that centres justice and the welfare of disproportionately impacted communities. We urge the machine learning community to pay close attention to the direct and indirect impact of our work on society, especially on vulnerable groups. Awareness of historical antecedents, contextual, and political dimensions of current work is imperative in this regard. We hope this work contributes to raising awareness and adds to a continued discussion of ethics and justice in ML.

[14]Obtained using *GloVe embeddings* [61] on the labels
[15]Listed in `df_hand_survey.csv`
[16]Link: `https://rb.gy/zccdps`

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