
DATACOMP:

In search of the next generation of multimodal datasets

Samir Yitzhak Gadre^{*2}, Gabriel Ilharco^{*1}, Alex Fang^{*1}, Jonathan Hayase¹,
Georgios Smyrnis⁵, Thao Nguyen¹, Ryan Marten^{7,9}, Mitchell Wortsman¹,
Dhruba Ghosh¹, Jieyu Zhang¹, Eyal Orgad³, Rahim Entezari¹⁰, Giannis Daras⁵,
Sarah Pratt¹, Vivek Ramanujan¹, Yonatan Bitton¹¹, Kalyani Marathe¹,
Stephen Mussmann¹, Richard Vencu⁶, Mehdi Cherti^{6,8}, Ranjay Krishna¹,
Pang Wei Koh^{1,12}, Olga Saukh¹⁰, Alexander Ratner^{1,13}, Shuran Song²,
Hannaneh Hajishirzi^{1,7}, Ali Farhadi¹, Romain Beaumont⁶,
Sewoong Oh¹, Alex Dimakis⁵, Jenia Jitsev^{6,8},
Yair Carmon³, Vaishaal Shankar⁴, Ludwig Schmidt^{1,6,7}

Abstract

Multimodal datasets are a critical component in recent breakthroughs such as CLIP, Stable Diffusion and GPT-4, yet their design does not receive the same research attention as model architectures or training algorithms. To address this shortcoming in the machine learning ecosystem, we introduce DATACOMP, a testbed for dataset experiments centered around a new candidate pool of 12.8 billion image-text pairs from Common Crawl. Participants in our benchmark design new filtering techniques or curate new data sources and then evaluate their new dataset by running our standardized CLIP training code and testing the resulting model on 38 downstream test sets. Our benchmark consists of multiple compute scales spanning four orders of magnitude, which enables the study of scaling trends and makes the benchmark accessible to researchers with varying resources. Our baseline experiments show that the DATACOMP workflow leads to better training sets. Our best baseline, DATACOMP-1B, enables training a CLIP ViT-L/14 from scratch to 79.2% zero-shot accuracy on ImageNet, outperforming OpenAI’s CLIP ViT-L/14 by 3.7 percentage points while using the same training procedure and compute. We release DATACOMP and all accompanying code at www.datacomp.ai.

1 Introduction

Recent advances in multimodal learning such as CLIP [111], DALL-E [115, 116], Stable Diffusion [123], Flamingo [8], and GPT-4 [103] offer unprecedented generalization capabilities in zero-shot classification, image generation, and in-context learning. While these advances use different algorithmic techniques, e.g., contrastive learning, diffusion, or auto-regressive modeling, they all rest on a common foundation: large datasets containing paired image-text examples. For instance, CLIP’s training set contains 400 million image-text pairs, and Stable Diffusion was trained on the two billion examples from LAION-2B [129]. This new generation of image-text datasets is 1,000 times larger than previous datasets such as ImageNet, which contains 1.2M images [37, 126].

Despite the central role of image-text datasets, little is known about them. Many state-of-the-art datasets are proprietary, and even for public datasets such as LAION-2B [129], it is unclear how design choices such as the data source or filtering techniques affect the resulting models. While there are thousands of ablation studies for algorithmic design choices (loss function, model architecture, etc.), datasets are often treated as monolithic artifacts without detailed investigation. Moreover,

^{*}Equal contribution, randomly ordered. Correspondence to contact@datacomp.ai. ¹University of Washington ²Columbia University ³Tel Aviv University ⁴Apple ⁵UT Austin ⁶LAION ⁷AI2 ⁸Juelich Supercomputing Center, Research Center Juelich ⁹University of Illinois Urbana-Champaign ¹⁰Graz University of Technology ¹¹Hebrew University ¹²Google Research ¹³Snorkel AI

Table 1: Zero-shot performance of CLIP models trained on different datasets. DATACOMP-1B, assembled with a simple filtering procedure on image-text pairs from Common Crawl, leads to a model with higher accuracy than previous results while using the same number of multiply-accumulate operations (MACs) or less during training. See Section 3.5 for details on the evaluation datasets.

Dataset	Dataset size	# samples seen	Architecture	Train compute (MACs)	ImageNet accuracy
OpenAI’s WIT [111]	0.4B	13B	ViT-L/14	1.1×10^{21}	75.5
LAION-400M [128, 28]	0.4B	13B	ViT-L/14	1.1×10^{21}	72.8
LAION-2B [129, 28]	2.3B	13B	ViT-L/14	1.1×10^{21}	73.1
LAION-2B [129, 28]	2.3B	34B	ViT-H/14	6.5×10^{21}	78.0
LAION-2B [129, 28]	2.3B	34B	ViT-g/14	9.9×10^{21}	78.5
DATACOMP-1B (ours)	1.4B	13B	ViT-L/14	1.1×10^{21}	79.2

datasets currently lack the benchmark-driven development process that has enabled a steady stream of improvements on the model side and isolates data enhancements from changes to the model. These issues impede further progress in multimodal learning, as evidenced by recent work showing that public datasets currently do not match the scaling behavior of proprietary alternatives [28].

In this paper, we take a step towards a more rigorous dataset development process. Our first and central contribution is **DATACOMP, a new benchmark for multimodal dataset design**. DATACOMP flips the traditional benchmarking paradigm in machine learning where the dataset is fixed and researchers propose new training algorithms. Instead, we hold the entire training code and computational budget constant so that participants innovate by proposing new training sets. To evaluate the quality of a training set, we score the resulting model with a testbed of 38 classification and retrieval tasks such as ImageNet [37], ImageNetV2 [121], DTD [30], EuroSAT [63], SUN-397 [146], and MSCOCO [26].

DATACOMP focuses on two key challenges that arise when assembling large training datasets: what data sources to train on, and how to filter a given data source. Each challenge corresponds to one track in our benchmark. To facilitate the *filtering track*, our second contribution is **COMMONPOOL, a dataset of 12.8B image-text pairs collected from Common Crawl** and currently the largest public image-text dataset. We release CommonPool as an index of image url-text pairs under a CC-BY-4.0 license, and apply content checks in its construction to remove unsafe or unwanted content. In the *filtering track*, the goal of participants is to find the best subset of COMMONPOOL to train on. In the second track, *Bring Your Own Data* (BYOD), participants may leverage any data source, as long as it does not overlap with our evaluation testbed.

Our third contribution is an investigation of **scaling trends for dataset design**. In particular, DATACOMP contains *four* scales, where we vary the training budget and the candidate pool size from 12.8M to 12.8B samples (see Table 2). Expressed in GPU hours, the cost of a single training run ranges from 4 to 40,000 GPU hours on the A100 cluster we used for development. The different scales enable researchers with different resources to participate in our benchmark. Moreover, our results show that the ranking of filtering approaches is largely consistent across scale.

Our fourth contribution is **over three hundred baseline experiments**, including techniques such as querying captions for relevant keywords, filtering based on image embeddings, and applying a threshold on CLIP scores. A key result from our baselines experiments is that smaller, more stringently filtered datasets can lead to models that generalize *better* than larger datasets coming from the same pool. At the 12.8B scale, our best filtering baseline increases ImageNet zero-shot accuracy by 6.9 percentage points (pp) relative to the unfiltered pool (see Table 3). For the BYOD track, our initial experiments show that 109M additional data points (less than 1% of the 12.8B pool) improve the CLIP-filtered subsets of COMMONPOOL by up to 1.2 pp ImageNet accuracy (see Table 18).

Finally, our fifth contribution is **DATACOMP-1B, a new state-of-the-art multimodal dataset**. We obtain DATACOMP-1B by combining our two most promising filtering baselines. DATACOMP-1B enables training a CLIP ViT-L/14 model to an ImageNet zero-shot accuracy of 79.2% (see Table 1), corresponding to a $9\times$ computational cost reduction when compared to a larger CLIP ViT-g/14 model trained on LAION-2B for about $3\times$ longer. Moreover, our model outperforms OpenAI’s original CLIP ViT-L/14 by 3.7 percentage points, while using the same compute budget.

To make DATACOMP a shared environment for controlled dataset experiments, we publicly release our candidate pool url index, our tooling for assembling these pools, our filtering baselines, and our

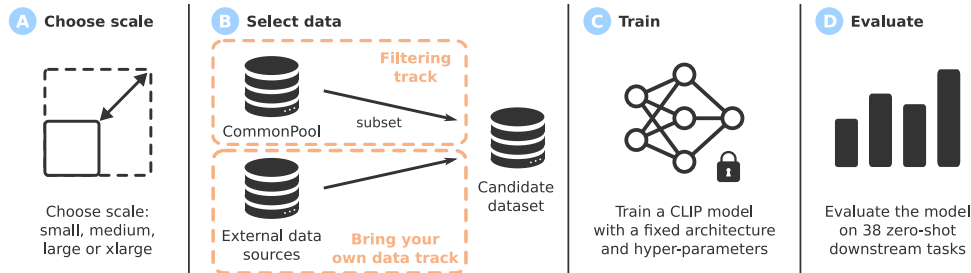


Figure 1: DATACOMP participant workflow. A) Choose a scale based on resource constraints. B) Design a dataset, in either the filtering or BYOD track. C) Train a CLIP model on the designed dataset using a fixed architecture and hyperparameters (Section 3.4). D) Evaluate the trained model on a suite of diverse downstream tasks (Section 3.5).

code for training and evaluating models at www.datacomp.ai. We believe that our infrastructure will help put research on dataset design on rigorous empirical foundations, draw attention to this understudied research area, and lead to the next generation of multimodal datasets.

2 Related Work

We review the most closely related work and include additional related work in Appendix C.

The effects of data curation. Classical work considers dataset cleaning and outlier removal [74, 152, 124, 125] to discard samples that may lead to undesirable model bias. A related line of work develops coreset selection algorithms [61, 7, 46, 11, 94, 145, 32], which aim to select data subsets that lead to the same performance as training on the entire dataset. These techniques appear to scale poorly to larger data regimes [51, 6]. More recent efforts in subset selection often operate on already curated datasets [98, 141, 130, 16, 33, 106] (e.g., CIFAR-10, ImageNet) or on smaller data regimes (e.g., YFCC-15M [111, 140]). These settings often do not reflect newer training paradigms that involve (1) *noisy* image-text pairs instead of category labeled images and (2) large scale datasets (e.g., billions of samples). While data-centric investigations have led to community competitions like DCBENCH [43] and DATAPERF [97], existing benchmarks have likewise operated at small data scales [100] compared to datasets like LAION-2B [129], which contains over two billion images. DATACOMP bridges this gap by aligning data-centric investigation with large scale image-text training.

There has also been renewed interest in dataset pruning and deduplication. Sorscher et al. [135] show that data pruning can improve traditional scaling trends on ImageNet, but do not consider image-text training or larger datasets. Raffel et al. [113] remove sentence redundancies when creating the C4 corpus. Subsequent work further demonstrated the benefits of deduplication for better language modeling [90]. Radenovic et al. [110] introduce CAT filtering for image-text datasets—a rule-based system to retain high quality samples. Abbas et al. [6] propose SemDeDup, which starts with the CAT-filtered LAION-440M subset, further employing clustering to remove semantic duplicates. DATACOMP facilitates data-centric investigation at an even larger scale (i.e., 12.8B sample scale) and provides a common experimental setting for fair comparison amongst dataset creation algorithms.

Large-scale multimodal datasets. Datasets have been instrumental to building multimodal models like CLIP [111], Flamingo [8], Stable Diffusion [123], DALL-E [115, 116] and GPT-4 [103]. These methods succeeded by training on large, heterogeneous datasets rather than solely through advanced modelling techniques. For example, OpenAI’s CLIP trains on 400M image-text pairs from the web, roughly $300\times$ the size of ImageNet [37]. Prior work on scaling image-text datasets also provides promising trends with respect to zero-shot model performance [73, 107]. Additional large scale datasets like FILIP-300M [149], FLD-900M [153], and PaLI-10B [25] were constructed to train multimodal models. However, many datasets used to train such models (including the dataset for OpenAI’s CLIP) are proprietary, making it hard to conduct data-centric investigations.

Even for public image-text datasets like SBU [104], Flickr30k [151], MS-COCO [26], TaiSu [92], Conceptual Captions [131], CC12M [24], RedCaps [38], WIT [136], Shutterstock [101], YFCC-

Table 2: Experimental configurations, with compute in multiply-accumulate operations (MACs).

Scale	Model	Train compute (MACs)	Pool size and # samples seen
small	ViT-B/32	9.5×10^{16}	12.8M
medium	ViT-B/32	9.5×10^{17}	128M
large	ViT-B/16	2.6×10^{19}	1.28B
xlarge	ViT-L/14	1.1×10^{21}	12.8B

100M [140], COYO-700M [20], LAION-400M [128], or LAION-2B [129] little is known about what constitutes a good image-text dataset. Preliminary analysis suggests that different image-text data sources lead to CLIP models with different properties [101]. However, previous work is limited to smaller scale data (10-15M examples). Birhane et al. [15] examine LAION-400M and find NSFW imagery and racial slurs, centering the dangers in web-scale multimodal datasets. To combat toxicity, we preprocess our pool to remove NSFW content and blur human faces detected in images. For more details on our safety preprocessing see Section 3.2, Appendices E and G.

3 The DATACOMP benchmark

DATACOMP is meant to facilitate data-centric experimentation. While traditional benchmarks emphasize model design, DATACOMP is centered around dataset development, where the resulting datasets can be used to train high accuracy models. We focus on large image-text datasets and quantify a dataset submission by training a CLIP model on it from scratch [111] and evaluating on 38 downstream image classification and retrieval tasks. We additionally have three secret test sets, which will be released after a year, to guard against overfitting. To facilitate such investigations, we provide a candidate pool of uncensored image-text pairs sourced from the public internet. Our benchmark offers two tracks: one where participants must filter samples from the pools we provide, and another where participants can use external data. Moreover, DATACOMP is structured to accommodate participants with diverse levels of computational resources: each track is broken down into four scales with varying compute requirements. We now discuss high-level design decisions, construction of a 12.8B image-text data pool to facilitate the competition, benchmark tracks, model training, and evaluation.

3.1 Competition design

Overview. In many areas of machine learning, larger datasets lead to better performing models [87, 79, 73, 107, 66, 28, 19, 111, 112]. Hence comparing only datasets with the same size is a natural starting point. However, this approach is flawed as controlling the dataset size ignores critical curation constraints: candidate pool size (i.e., number of image-text pairs to harvest) and training compute. For instance, assembling a dataset like LAION-2B consists of identifying *data sources* (e.g., Common Crawl or Reddit) and *filtering* the data source. Notably, *the final dataset size is a design choice* and is only upper-bounded by the data sources. Hence, the true data constraint is the size of the reservoir of samples: *candidate pool* to be filtered. To make DATACOMP a realistic benchmark, we therefore fix the candidate pool in the filtering track, but give participants control over the training set size.

Compute cost is another relevant constraint. To put datasets of different size on equal footing, we specify the total *number of training samples seen*. Consider the 12.8B compute scale and filtered datasets A and B , with 6.4B and 3.2B image-text pairs respectively. At this scale, we train by making two passes over A , while making four passes over B . A key result from our experiments is that smaller, more stringently filtered datasets can lead to models that generalize *better*.

Competition tracks. Two key procedures in assembling a training dataset are filtering a data source [128, 129, 20] and aggregating data sources [36, 37]. To reflect this structure, DATACOMP has two tracks: *filtering*, where participants select a subset of the samples from COMMONPOOL, and *Bring Your Own Data* (BYOD), where participants can use any source of data. Key decisions for each tracks are described in Sections 3.2 and 3.3, respectively. For full competition track rules see Appendix A.

Competition compute scales. To facilitate study of scaling trends and accommodate participants with various computational resources, we structure DATACOMP using four scales of compute: `small`, `medium`, `large` and `xlarge`. Each new scale increases the number of samples seen during training by

10× (from 12.8M to 12.8B samples seen), and the pool we provide by the same factor (from 12.8M samples to 12.8B samples). Table 2 gives the experimental configuration used for each scale. For the `small` scale, our runs took 4 hours on an A100 GPU, and for the `xlarge` scale 81 hours on 512 GPUs.

3.2 COMMONPOOL generation, for the filtering track

We construct a large-scale pool of image-text pairs, COMMONPOOL, from Common Crawl [3]. CommonPool is distributed as an image url-text pair index under a CC-BY-4.0 license. Our pool construction pipeline has four steps: url extraction and data download, NSFW detection, evaluation set deduplication, and face blurring. We additionally provide per sample metadata (e.g., CLIP features). Starting from the `xlarge` COMMONPOOL, we take successive random subsets to create `large`, `medium`, and `small` COMMONPOOL (e.g., `medium` is a subset of `large`).

Extracting urls and downloading data. We first use `cc2dataset` [1], which utilizes Apache Spark [155], to extract pairs of image urls and nonempty alt-text from all Common Crawl snapshots from 2014 to 2022. We then deduplicate the url-text pairs and randomly shuffle. This step results in ~88B possible samples. Not all samples are downloadable; other samples are not suitable due to NSFW content or overlap with our evaluation sets. We attempt to download ~40B samples using `img2dataset` [5] resulting in ~16.8B image-text pairs. For more details, see Appendix D.

Safety preprocessing. Since Common Crawl is a snapshot of the internet, we require strict preprocessing to remove unsafe content. We use Detoxify [60] to prune samples that contain unsafe text (e.g., obscene, sexually explicit, or threatening language). We also discard samples with explicit visual content. To do so, we train a classifier on CLIP ViT-L/14 [111] features, using the NSFW dataset used in LAION-5B [129]. We validate our classifier against the Google commercial image safety API. See Appendix E for details. Around 19% of image-text pairs are considered NSFW, taking the pool of ~16.8B downloads to ~13.6B samples.

Evaluation set deduplication. To prevent accidental overfitting to certain test sets in our evaluation suite, we perform a thorough near-duplicate removal between the candidate pool and our evaluation sets, using a state-of-the-art image deduplication model [150]. Appendix F contains additional details. The model flags ~3% of the 16.8B images as near-duplicates, reducing the ~13.6B pool to ~13.1B samples. From here we select a random subset to get the `xlarge` pool of 12.8B samples.

Face detection & blurring. To protect the privacy of individuals, we detect and blur faces from images in our pool using a face detector [53]. As observed by Yang et al. [148], obfuscating faces has little impact on model performance, as we also observe in our experiments (Appendix G).

Pool metadata. To bootstrap participants we distribute metadata for each sample in COMMONPOOL (e.g., image url, alt-text, original image resolution, CLIP features, and CLIP similarity scores). Following Carlini et al. [22], we release SHA256 hashes for each image to guard against data poisoning in subsequent COMMONPOOL downloads. For additional details see Appendix H. We open-source our metadata processing pipeline as `dataset2metadata` [4].

3.3 The bring your own data (BYOD) track

While COMMONPOOL can be used to study different filtering techniques, state-of-the-art models often train on data from different sources. For instance, the Flamingo model [8] uses both multimodal massive web (M3W) and ALIGN datasets [73]. To facilitate non-proprietary research on curating data from many sources, we instantiate a separate DATACOMP track to allow participants to combine multiple data streams. For example, participants could construct a training set from CC12M [24], YFCC100M [140], and data sources they label themselves. In Section 4.2 and Appendix P.2 we describe our exploration using existing public, image-text datasets. These datasets are acquired from their respective sources and are not re-release as part of DATACOMP.

3.4 Training

We create a common experimental setting that enables comparable experiments by fixing the training procedure. We closely follow the CLIP training recipe proposed by Radford et al. [111]: training

models from scratch with a contrastive objective over images and captions. Given a set of image-caption pairs, we train an image encoder and a text encoder such that the similarity between the representations of images and their corresponding text is maximized relative to unaligned pairs.¹ For each scale, we fix the model architecture and hyperparameters (see Table 2). We pick Vision Transformers (ViTs) [39] as the image encoder, considering the better scaling trends observed by Radford et al. [111] compared to ResNets [62]. Models are trained for a fixed number of steps determined by the scale (Table 2), using the OpenCLIP repository [69]. See Appendix N for details.

3.5 Evaluation

We evaluate on a suite of 38 image classification and retrieval tasks. We also study two additional fairness tasks, detailed in Section 5 and Appendix Q. As discussed in Section 3.2, we remove test set images from DATACOMP to avoid contamination. Image classification datasets range from satellite imagery recognition to classifying metastatic tissues. In total we have (with some overlap): 22 of the datasets evaluated in Radford et al. [111], 6 ImageNet distribution shifts (i.e., ImageNet-Sketch [143], ImageNet-V2 [121], ImageNet-A [65], ImageNet-O [65], ImageNet-R [64], and ObjectNet [13]), 13 datasets from VTAB [156], and 3 datasets from WILDS [83, 127]. Retrieval datasets include Flickr30k [151], MSCOCO [26], and the WinoGAViL commonsense association task [17]. To aggregate results over all evaluation tasks, we average the preferred metric for each task.

DATACOMP adopts a zero-shot evaluation protocol: models are tested without training on the evaluation tasks. This approach is computationally efficient and measures a model’s ability to perform well without any additional training. We find a strong rank correlation (>0.99) between performance in linear probe zero-shot settings (Appendix Figure 16). Additional details are in Appendix O.

4 Baselines

4.1 Filtering baselines

We study six simple filtering methods for the filtering track; see Appendix P.1 for further details.

No filtering. We simply use the entire pool as the subset, without any filtering. Since each pool size is equal to the sample budget, training consists of one pass over the data.

Random subsets. To isolate the effects of increasing the compute budget from increasing the dataset size, we form subsets consisting of 1%, 10%, 25%, 50% and 75% of the pool chosen at random.

Basic filtering. We consider many simple filtering operations inspired by Schuhmann et al. [128] and Byeon et al. [20]: filtering by *language* (English captions, using either fasttext [77] or cld3 [2]); filtering by *caption length* (over two words and five characters); and filtering by *image size* (smaller dimension above 200 pixels and aspect ratio below three). We also experiment with combining language and caption length filtering and combining language, caption length, image size filtering. Unless otherwise specified, “basic” refers fasttext English, caption length, and image size filtering.

CLIP score and LAION filtering. We experiment with CLIP score filtering (also employed by LAION), where we take only examples having cosine similarity scores between CLIP image and text embeddings that exceed a pre-defined threshold. We investigate a range of thresholds and two OpenAI CLIP models for computing the scores: the ViT-B/32 model (as in LAION) and the larger ViT-L/14. We also combine CLIP score thresholds and cld3 English filtering to reproduce the LAION-2B filtering scheme. Table 16 in Appendix P.1 summarizes the different CLIP score configurations.

Text-based filtering. We select examples that contain text overlapping with ImageNet class names, which serve as a proxy for relevance to downstream tasks. Specifically, we select English captions (according to fasttext) that contain words from ImageNet-21K or ImageNet-1K [37] class synsets.

¹More precisely, given a batch of data $\{(x_1, y_1), \dots, (x_B, y_B)\}$ with images x and captions y , we train the image encoder g and text encoder v with the loss $\ell = \frac{1}{2} \sum_{i=1}^B \frac{\sigma_{ii}}{\sum_{j=1}^B \sigma_{ij}} + \frac{1}{2} \sum_{i=1}^B \frac{\sigma_{ii}}{\sum_{j=1}^B \sigma_{ji}}$, where $\sigma_{ij} = \exp \langle g(x_i), h(y_j) \rangle$. We also use a learnable temperature parameter as in Radford et al. [111].

Table 3: Zero-shot performance for select baselines in the *filtering* track. On all scales, filtering strategies lead to better performance than using the entire, unfiltered pool. The intersection between imaged-based and CLIP score strategies performs well on most tasks and scales. For all metrics, higher is better (see Appendix O for details). \cap denotes the intersection of filtering strategies.

Scale	Filtering strategy	Dataset size	Samples seen	ImageNet	ImageNet dist. shifts	VTAB	Retrieval	Average over 38 datasets
small	No filtering	12.8M	12.8M	0.025	0.033	0.145	0.114	0.132
	Basic filtering	3M	12.8M	0.038	0.043	0.150	0.118	0.142
	Text-based	3.2M	12.8M	0.046	0.052	0.169	<u>0.125</u>	0.157
	Image-based	3M	12.8M	0.043	0.047	0.178	0.121	0.159
	LAION-2B filtering	1.3M	12.8M	0.031	0.040	0.136	0.092	0.133
	CLIP score (L/14 30%)	3.8M	12.8M	<u>0.051</u>	<u>0.055</u>	<u>0.190</u>	0.119	<u>0.173</u>
	Image-based \cap CLIP score (L/14 30%)	1.4M	12.8M	0.039	0.045	0.162	0.094	0.144
medium	No filtering	128M	128M	0.176	0.152	0.259	0.219	0.258
	Basic filtering	30M	128M	0.226	0.193	0.284	0.251	0.285
	Text-based	31M	128M	0.255	0.215	0.328	0.249	0.307
	Image-based	29M	128M	0.268	0.213	0.319	<u>0.256</u>	0.312
	LAION-2B filtering	13M	128M	0.230	0.198	0.307	0.233	0.292
	CLIP score (L/14 30%)	38M	128M	0.273	0.230	0.338	0.251	<u>0.328</u>
	Image-based \cap CLIP score (L/14 30%)	14M	128M	<u>0.297</u>	<u>0.239</u>	<u>0.346</u>	0.231	<u>0.328</u>
large	No filtering	1.28B	1.28B	0.459	0.378	0.426	0.419	0.437
	Basic filtering	298M	1.28B	0.516	0.423	0.446	0.480	0.458
	Text-based	317M	1.28B	0.561	0.465	0.465	0.352	0.466
	Image-based	293M	1.28B	0.572	0.454	0.483	0.479	0.476
	LAION-2B filtering	130M	1.28B	0.553	0.453	0.510	0.495	0.501
	CLIP score (L/14 30%)	384M	1.28B	0.578	0.474	0.538	0.466	0.529
	Image-based \cap CLIP score (L/14 30%)	140M	1.28B	<u>0.631</u>	<u>0.508</u>	<u>0.546</u>	<u>0.498</u>	<u>0.537</u>
xlarge	No filtering	12.8B	12.8B	0.723	0.612	0.611	0.569	0.621
	LAION-2B filtering	1.3B	12.8B	0.755	0.637	0.624	<u>0.620</u>	0.636
	CLIP score (L/14 30%)	3.8B	12.8B	0.764	0.655	0.643	0.588	0.650
	Image-based \cap CLIP score (L/14 30%)	1.4B	12.8B	<u>0.792</u>	<u>0.679</u>	<u>0.652</u>	0.608	<u>0.663</u>

Image-based filtering. We select a subset of examples whose visual content overlaps with ImageNet classes. After applying English language (fasttext) and caption length filtering, we cluster the image embeddings extracted by the OpenAI ViT-L/14 model for each image into 100K groups using Faiss [75]. We then find the nearest neighbor group for every ImageNet training example, and keep examples belonging to these groups. We apply this procedure using either ImageNet-21K (14M images) or ImageNet-1K (1.2M images), forming two subsets.

4.2 BYOD baselines

We experiment with multiple external data sources, including four moderately sized datasets (10 to 58M samples) studied by Nguyen et al. [101]—CC12M [24], YFCC15M [140, 111], RedCaps [38] and Shutterstock [101]—and the larger LAION-2B [129]. Additional experiments, along with more details about the data sources are provided in Appendix P.2. We consider these data sources as they are and do not perform additional preprocessing. We also present experiments combining some of the data sources (using only the external datasets, or in addition to data from our pool).

5 Results and discussion

5.1 Building better datasets

Main results. Our key results are in Table 3. Most notably, the intersection between image-based filtering and CLIP score filtering excels on most tasks. The exception is at the `small` scale and for retrieval datasets.² Furthermore, other filtering strategies like basic, CLIP score, image-based, text-based filtering show better downstream performance when compared to no filtering. A much larger suite of experiment results can be found in Appendix R.

DATA COMP leads to better image-text datasets. We hope DATA COMP catalyzes the search for the next generation of multimodal datasets. We contribute DATA COMP-1B, which is the output of the Image-based \cap CLIP score (L/14 30%) baseline filter at the `xlarge` scale of the filtering track.

²Cherti et al. [28] also observe that models rank differently on classification and retrieval tasks.

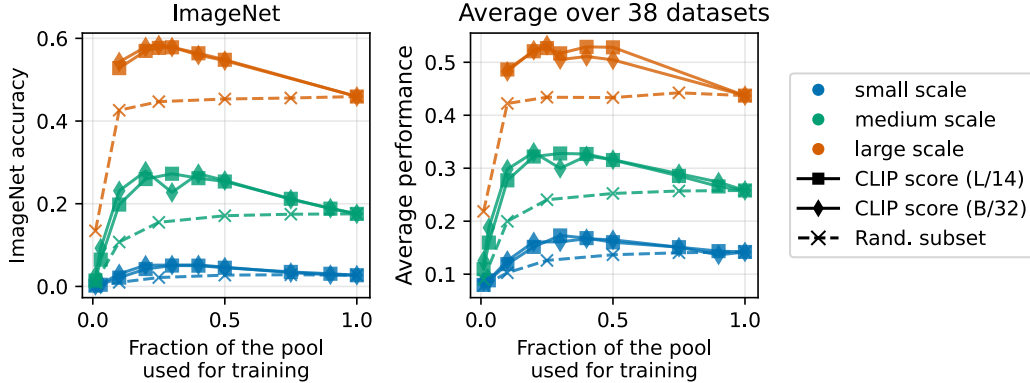


Figure 2: Performance of random subsets (dotted line) and CLIP score filtering (solid line) when varying the subset size. When taking random subsets, larger subsets are always better. For CLIP score filtering, subsets with intermediate size perform best.

Our dataset is comprised of 1.4B samples, which not only is *smaller* than the LAION-2B dataset with 2.3B samples, but also comes from a smaller pool. Nevertheless, a CLIP L/14 trained on DATACOMP-1B outperforms the LAION-2B competitor by 6.1 percentage points on ImageNet (see Table 1). Moreover, training on DATACOMP-1B improves ImageNet accuracy by 3.7 percentage points over OpenAI’s ViT-L/14 trained with the same compute budget. Additionally, even if we restrict ourselves to 400M samples, we can still find a subset of DATACOMP-1B that outperforms OpenAI’s ViT-L/14, as seen in Table 24. These results demonstrate the impact that DATACOMP can make and provide a foundation upon which participants can build.

External data sources can improve performance. Appendix P.2 Table 18 shows results for several baselines in the BYOD track. We find several instances where adding external data sources improves performance over using just data from COMMONPOOL. For example, at the `large` scale, combining CLIP-filtered data from COMMONPOOL with external data from CC12M [24], YFCC15M [140, 111], RedCaps [38] and Shutterstock [101] boosts ImageNet accuracy by 4.3 percentage points. See Appendix P.2 for more experiments and details.

Trade-off between data diversity and repetition. In Figure 2, we see that randomly selecting subsets of the pool has little effect and degrades performance substantially when only small fractions are used. When filtering with CLIP scores, the optimal training set comes from selecting $\sim 30\%$ of the pool with the highest scores. The difference in performance trends between random subsets and CLIP score filtering highlights the importance of filtering strategies for selecting samples.

5.2 DATACOMP design analyses

COMMONPOOL and LAION are comparable with the same filtering. To validate our pool construction, we show that we can build datasets comparable to LAION-2B by employing their filtering technique on our pool. LAION-2B selects all samples where the caption is in English and the cosine similarity score from a trained ViT-B/32 CLIP model is above 0.28. We compare this filtering approach on our pool using the same number samples, 130M samples at the `large` scale. We find that the different data sources perform comparably: 55.3% vs 55.7% accuracy on ImageNet, and 0.501 vs 0.489 average performance over our evaluation sets using our pool and LAION-2B, respectively.

Consistency across scales. We find that the ranking between filtering strategies is typically consistent across different scales. This is illustrated in Figure 3, which shows that the baselines at `small` and `medium` scales are positively correlated. Moreover, as shown in Appendix Table 22, the rank correlations of performance is high, between 0.71 and 0.90 for different scale pairs.

Consistency across training changes. DATACOMP fixes the training procedure, so a natural question is whether better datasets from DATACOMP are better outside of DATACOMP. While DATACOMP-1B is trained at the `xlarge` scale, we show in Appendix Table 23 that even when substituting the ViT-L/14

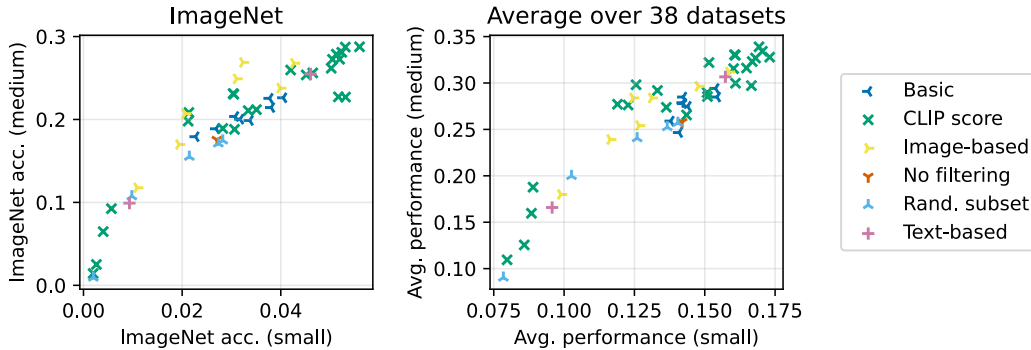


Figure 3: Correlation between `small` and `medium` scale baselines. Smaller scales can serve as useful guides for larger scales. Results for additional scales are shown in Appendix Figure 22.

for a ViT-B/16 or ViT-B/32, training on DATACOMP-1B outperforms training on OpenAI’s WIT and LAION-2B. Additionally, we found that modifying hyperparameters such as training steps and batch size minimally affects the relative ordering of different data curation methods on downstream performance. Details on hyperparameter ablations are in Appendix L.

5.3 Evaluation trends

ImageNet accuracy is indicative, but not the complete picture. Similarly to Kornblith et al. [84], in Appendix Figure 25 we find that ImageNet performance is highly correlated with the average performance across all datasets we study, with an overall correlation of 0.99.³ However, ImageNet performance is not representative of all evaluation tasks, as the correlation between ImageNet accuracy and accuracy on other individual datasets varies substantially, in some cases even exhibiting a negative correlation, as discussed in Appendix R.

Robustness and fairness. While typical models trained on a target task suffer large performance drops under data distribution shift, zero-shot CLIP models are known to exhibit strong performance across many distributions [111]. In Appendix Figure 26, we show that CLIP models trained with data from our pool are more robust to distribution shift than ImageNet-trained models from Taori et al. [139]’s testbed. Examining geographic diversity, we find that our models are better than ImageNet-trained models, but fall short of models fine-tuned on diverse curated datasets (see Appendix Figure 21). We also perform a face classification analysis and identify demographic biases in our models: notably, the BYOD datasets we consider can increase the risk of misclassification. See Appendix Q for more fairness and diversity analyses.

6 Limitations and conclusion

In terms of societal risks, creating an index of image-text pairs from the public internet can be problematic. The internet contains unsafe, toxic, and sensitive content, which ideally should not percolate into machine learning datasets. Though we take steps to remove NSFW content and blur human faces to protect privacy, we hope future work will further explore the biases and risks from COMMONPOOL and DATACOMP-1B. We see several additional directions for future work, including 1) Curating more data sources. 2) Improved data filtering algorithms. 3) Further supervision signals (e.g., image captions coming from captioning models). 4) Additional input modalities (e.g., video, 3D objects). 5) Broader evaluations for vision-and-language and robotics tasks.

Overall, we see DATACOMP as a first step towards improving training datasets, and hope our new benchmark will foster further research. By providing a controlled experimental setting, DATACOMP enables researchers to iterate on dataset design on rigorous empirical foundations. We open-source all of our code, data, and infrastructure, and hope these resources will help the community build the next generation of multimodal datasets.

³Note that unlike Kornblith et al. [84] we evaluate zero-shot performance rather than transfer learning.

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⁴<https://gauss-centre.eu>

References

- [1] cc2dataset. <https://github.com/rom1504/cc2dataset>.
- [2] CLD3. <https://github.com/google/cld3>.
- [3] Common Crawl. <https://commoncrawl.org>.
- [4] dataset2metadata. <https://github.com/mlfoundations/dataset2metadata>.
- [5] img2dataset. <https://github.com/rom1504/img2dataset>.
- [6] Amro Abbas, Kushal Tirumala, Dániel Simig, Surya Ganguli, and Ari S Morcos. Semdedup: Data-efficient learning at web-scale through semantic deduplication, 2023. <https://arxiv.org/abs/2303.09540>.
- [7] Pankaj K. Agarwal, Sarel Har-Peled, and Kasturi R. Varadarajan. Approximating extent measures of points. *Journal of the ACM (JACM)*, 2004. <https://doi.org/10.1145/1008731.1008736>.
- [8] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katie Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022. <https://openreview.net/forum?id=EbMuimAbPbs>.
- [9] Abhijeet Awasthi, Sabyasachi Ghosh, Rasna Goyal, and Sunita Sarawagi. Learning from rules generalizing labeled exemplars. In *International Conference on Learning Representations (ICLR)*, 2020. <https://openreview.net/forum?id=SkeuexBtDr>.
- [10] Stephen H Bach, Daniel Rodriguez, Yintao Liu, Chong Luo, Haidong Shao, Cassandra Xia, Souvik Sen, Alex Ratner, Braden Hancock, Houman Alborzi, Rahul Kuchhal, Christopher Ré, and Rob Malkin. Snorkel drybell: A case study in deploying weak supervision at industrial scale. In *Special Interest Group on Management of Data (SIGMOD)*, 2019. <https://arxiv.org/abs/1812.00417>.
- [11] Olivier Bachem, Mario Lucic, and Andreas Krause. Coresets for nonparametric estimation - the case of dp-means. In *International Conference on Machine Learning (ICML)*, 2015. <https://proceedings.mlr.press/v37/bachem15.html>.
- [12] Peter Bandi, Oscar Geessink, Quirine Manson, Marcory Van Dijk, Maschenka Balkenhol, Meyke Hermsen, Babak Ehteshami Bejnordi, Byungjae Lee, Kyunghyun Paeng, Aoxiao Zhong, et al. From detection of individual metastases to classification of lymph node status at the patient level: the camelyon17 challenge. *IEEE Transactions on Medical Imaging*, 2018. <https://pubmed.ncbi.nlm.nih.gov/30716025/>.
- [13] Andrei Barbu, David Mayo, Julian Alverio, William Luo, Christopher Wang, Dan Gutfreund, Josh Tenenbaum, and Boris Katz. Objectnet: A large-scale bias-controlled dataset for pushing the limits of object recognition models. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett (eds.), *Advances in Neural Information Processing Systems (NeurIPS)*, volume 32. Curran Associates, Inc., 2019. <https://proceedings.neurips.cc/paper/2019/file/97af07a14cacba681feacf3012730892-Paper.pdf>.
- [14] Sara Beery, Elijah Cole, and Arvi Gjoka. The iwildcam 2020 competition dataset, 2020. <https://arxiv.org/abs/2004.10340>.
- [15] Abeba Birhane, Vinay Uday Prabhu, and Emmanuel Kahembwe. Multimodal datasets: misogyny, pornography, and malignant stereotypes. 2021. <https://arxiv.org/abs/2110.01963>.
- [16] Vighnesh Birodkar, Hossein Mobahi, and Samy Bengio. Semantic redundancies in image-classification datasets: The 10% you don't need. *arXiv preprint arXiv:1901.11409*, 2019. <https://arxiv.org/abs/1901.11409>.
- [17] Yonatan Bitton, Nitzan Bitton Guetta, Ron Yosef, Yuval Elovici, Mohit Bansal, Gabriel Stanovsky, and Roy Schwartz. WinoGAViL: Gamified association benchmark to challenge vision-and-language models, 2022. <https://arxiv.org/abs/2207.12576>.
- [18] Lukas Bossard, Matthieu Guillaumin, and Luc Van Gool. Food-101—mining discriminative components with random forests. In *European Conference on Computer Vision (ECCV)*, 2014. https://link.springer.com/chapter/10.1007/978-3-319-10599-4_29.

- [19] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (eds.), *Advances in Neural Information Processing Systems (NeurIPS)*, 2020. https://proceedings.neurips.cc/paper_files/paper/2020/file/1457c0d6bfc4967418bfb8ac142f64a-Paper.pdf.
- [20] Minwoo Byeon, Beomhee Park, Haecheon Kim, Sungjun Lee, Woonhyuk Baek, and Saehoon Kim. Coyo-700m: Image-text pair dataset. <https://github.com/kakaobrain/coyo-dataset>, 2022.
- [21] Ethan Caballero, Kshitij Gupta, Irina Rish, and David Krueger. Broken neural scaling laws. *International Conference on Learning Representations (ICLR)*, 2023. <https://arxiv.org/abs/2210.14891>.
- [22] Nicholas Carlini, Matthew Jagielski, Christopher A Choquette-Choo, Daniel Paleka, Will Pearce, Hyrum Anderson, Andreas Terzis, Kurt Thomas, and Florian Tramèr. Poisoning web-scale training datasets is practical, 2023. <https://arxiv.org/abs/2302.10149>.
- [23] Stephanie C. Y. Chan, Adam Santoro, Andrew K. Lampinen, Jane X. Wang, Aaditya Singh, Pierre H. Richemond, Jay McClelland, and Felix Hill. Data distributional properties drive emergent in-context learning in transformers. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022. <https://arxiv.org/abs/2205.05055>.
- [24] Soravit Changpinyo, Piyush Sharma, Nan Ding, and Radu Soricut. Conceptual 12m: Pushing web-scale image-text pre-training to recognize long-tail visual concepts. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021. <https://arxiv.org/abs/2102.08981>.
- [25] Xi Chen, Xiao Wang, Soravit Changpinyo, AJ Piergiovanni, Piotr Padlewski, Daniel Salz, Sebastian Goodman, Adam Grycner, Basil Mustafa, Lucas Beyer, Alexander Kolesnikov, Joan Puigcerver, Nan Ding, Keran Rong, Hassan Akbari, Gaurav Mishra, Linting Xue, Ashish Thapliyal, James Bradbury, Weicheng Kuo, Mojtaba Seyedhosseini, Chao Jia, Burcu Karagol Ayan, Carlos Riquelme, Andreas Steiner, Anelia Angelova, Xiaohua Zhai, Neil Houlsby, and Radu Soricut. Pali: A jointly-scaled multilingual language-image model. In *International Conference on Learning Representations (ICLR)*, 2022. <https://arxiv.org/abs/2209.06794>.
- [26] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C Lawrence Zitnick. Microsoft COCO captions: Data collection and evaluation server, 2015. <https://arxiv.org/abs/1504.00325>.
- [27] Gong Cheng, Junwei Han, and Xiaoqiang Lu. Remote sensing image scene classification: Benchmark and state of the art. *Proceedings of the Institute of Electrical and Electronics Engineers (IEEE)*, 2017. <https://ieeexplore.ieee.org/abstract/document/7891544>.
- [28] Mehdi Cherti, Romain Beaumont, Ross Wightman, Mitchell Wortsman, Gabriel Ilharco, Cade Gordon, Christoph Schuhmann, Ludwig Schmidt, and Jenia Jitsev. Reproducible scaling laws for contrastive language-image learning, 2022. <https://arxiv.org/abs/2212.07143>.
- [29] Gordon Christie, Neil Fendley, James Wilson, and Ryan Mukherjee. Functional map of the world. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018. <https://arxiv.org/abs/1711.07846>.
- [30] Mircea Cimpoi, Subhansu Maji, Iasonas Kokkinos, Sammy Mohamed, and Andrea Vedaldi. Describing textures in the wild. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014. https://openaccess.thecvf.com/content_cvpr_2014/html/Cimpoi_Describing_Textures_in_2014_CVPR_paper.html.
- [31] Adam Coates, Andrew Ng, and Honglak Lee. An analysis of single-layer networks in unsupervised feature learning. In *International Conference on Artificial Intelligence and Statistics (AISTATS)*, 2011. <https://proceedings.mlr.press/v15/coates11a.html>.

- [32] Michael B. Cohen, Cameron Musco, and Christopher Musco. Input sparsity time low-rank approximation via ridge leverage score sampling. In *ACM-SIAM Symposium on Discrete Algorithms*, 2017. <https://dl.acm.org/doi/10.5555/3039686.3039801>.
- [33] C Coleman, C Yeh, S Mussmann, B Mirzasoleiman, P Bailis, P Liang, J Leskovec, and M Zaharia. Selection via proxy: Efficient data selection for deep learning. In *International Conference on Learning Representations (ICLR)*, 2020. <https://arxiv.org/abs/1906.11829>.
- [34] Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. Unsupervised cross-lingual representation learning at scale. In *Annual Meeting of the Association for Computational Linguistics (ACL)*, 2019. <https://arxiv.org/abs/1911.02116>.
- [35] R Dennis Cook. Detection of influential observation in linear. *Technometrics*, 19(1):15–18, 1977.
- [36] Achal Dave, Tarasha Khurana, Pavel Tokmakov, Cordelia Schmid, and Deva Ramanan. Tao: A large-scale benchmark for tracking any object. In *European Conference on Computer Vision (ECCV)*, 2020. <https://arxiv.org/abs/2005.10356>.
- [37] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2009. <https://ieeexplore.ieee.org/abstract/document/5206848>.
- [38] Karan Desai, Gaurav Kaul, Zubin Aysola, and Justin Johnson. Redcaps: Web-curated image-text data created by the people, for the people, 2021. <https://arxiv.org/abs/2111.11431>.
- [39] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations (ICLR)*, 2021. <https://openreview.net/forum?id=YicbFdNTTy>.
- [40] Matthijs Douze, Giorgos Tolias, Ed Pizzi, Zoë Papanikolaou, Lowik Chanussot, Filip Radenovic, Tomas Jenicek, Maxim Maximov, Laura Leal-Taixé, Ismail Elezi, Ondrej Chum, and Cristian Canton-Ferrer. The 2021 image similarity dataset and challenge, 2021. <https://arxiv.org/abs/2106.09672>.
- [41] Kawin Ethayarajh, Yejin Choi, and Swabha Swayamdipta. Understanding dataset difficulty with v-usable information. In *International Conference on Machine Learning (ICML)*, 2022. <https://arxiv.org/abs/2110.08420>.
- [42] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The PASCAL Visual Object Classes Challenge 2007 (VOC2007) Results, 2007. <http://www.pascal-network.org/challenges/VOC/voc2007/workshop/index.html>.
- [43] Sabri Eyuboglu, Bojan Karlaš, Christopher Ré, Ce Zhang, and James Zou. dcbench: a benchmark for data-centric ai systems. In *Proceedings of the Sixth Workshop on Data Management for End-To-End Machine Learning*, 2022. <https://dl.acm.org/doi/abs/10.1145/3533028.3533310>.
- [44] Alex Fang, Gabriel Ilharco, Mitchell Wortsman, Yuhao Wan, Vaishal Shankar, Achal Dave, and Ludwig Schmidt. Data determines distributional robustness in contrastive language image pre-training (clip). In *International Conference on Machine Learning (ICML)*, 2022. <https://arxiv.org/abs/2205.01397>.
- [45] Li Fei-Fei, Rob Fergus, and Pietro Perona. Learning generative visual models from few training examples: An incremental Bayesian approach tested on 101 object categories. *Conference on Computer Vision and Pattern Recognition (CVPR) Workshop*, 2004. <https://ieeexplore.ieee.org/document/1384978>.
- [46] Dan Feldman, Matthew Faulkner, and Andreas Krause. Scalable training of mixture models via coresets. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2011. https://proceedings.neurips.cc/paper_files/paper/2011/file/2b6d65b9a9445c4271ab9076ead5605a-Paper.pdf.

- [47] Daniel Y. Fu, Mayee F. Chen, Frederic Sala, Sarah M. Hooper, Kayvon Fatahalian, and Christopher Ré. Fast and three-rious: Speeding up weak supervision with triplet methods. In *International Conference on Machine Learning (ICML)*, 2020. <https://arxiv.org/abs/2002.11955>.
- [48] Andreas Geiger, Philip Lenz, and Raquel Urtasun. Are we ready for autonomous driving? the kitti vision benchmark suite. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2012. <https://ieeexplore.ieee.org/abstract/document/6248074>.
- [49] Amirata Ghorbani and James Zou. Data shapley: Equitable valuation of data for machine learning. In *International Conference on Machine Learning*, pp. 2242–2251. PMLR, 2019.
- [50] Stephan Graf and Olaf Mextorf. Just: Large-scale multi-tier storage infrastructure at the jülich supercomputing centre. *Journal of large-scale research facilities JLSRF*, 2021. <https://jlsrf.org/index.php/lsf/article/view/180>.
- [51] Chengcheng Guo, Bo Zhao, and Yanbing Bai. Deepcore: A comprehensive library for coresets selection in deep learning, 2022. <https://arxiv.org/abs/2204.08499>.
- [52] Han Guo, Nazneen Fatema Rajani, Peter Hase, Mohit Bansal, and Caiming Xiong. Fastif: Scalable influence functions for efficient model interpretation and debugging. 2020. <https://arxiv.org/abs/2012.15781>.
- [53] Jia Guo, Jiankang Deng, Alexandros Lattas, and Stefanos Zafeiriou. Sample and computation redistribution for efficient face detection. In *International Conference on Learning Representations (ICLR)*, 2021. <https://arxiv.org/abs/2105.04714>.
- [54] Agrim Gupta, Piotr Dollar, and Ross Girshick. LVIS: A dataset for large vocabulary instance segmentation. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019.
- [55] Suchin Gururangan, Swabha Swayamdipta, Omer Levy, Roy Schwartz, Samuel Bowman, and Noah A. Smith. Annotation artifacts in natural language inference data. In *Conference of the North American Chapter of the Association for Computational Linguistics (NAACL)*, 2018. <https://aclanthology.org/N18-2017>.
- [56] Kelvin Guu, Albert Webson, Ellie Pavlick, Lucas Dixon, Ian Tenney, and Tolga Bolukbasi. Simfluence: Modeling the influence of individual training examples by simulating training runs, 2023. <https://arxiv.org/abs/2303.08114>.
- [57] Frank R Hampel. The influence curve and its role in robust estimation. *Journal of the american statistical association*, 1974. <https://www.jstor.org/stable/2285666>.
- [58] Xiaochuang Han, Byron C Wallace, and Yulia Tsvetkov. Explaining black box predictions and unveiling data artifacts through influence functions, 2020. <https://arxiv.org/abs/2005.06676>.
- [59] A. Hanna, Emily L. Denton, Andrew Smart, and Jamila Smith-Loud. Towards a critical race methodology in algorithmic fairness. In *Conference on Fairness, Accountability, and Transparency (FAccT)*, 2020. <https://arxiv.org/abs/1912.03593>.
- [60] Laura Hanu and Unitary team. Detoxify, 2020. <https://github.com/unitaryai/detoxify>.
- [61] Sarel Har-Peled and Soham Mazumdar. On coresets for k-means and k-median clustering. In *Symposium on Theory of Computing (STOC)*, 2004. <https://doi.org/10.1145/1007352.1007400>.
- [62] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. <https://arxiv.org/abs/1512.03385>.
- [63] Patrick Helber, Benjamin Bischke, Andreas Dengel, and Damian Borth. Eurosat: A novel dataset and deep learning benchmark for land use and land cover classification. *Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2019. <https://arxiv.org/abs/1709.00029>.
- [64] Dan Hendrycks, Steven Basart, Norman Mu, Saurav Kadavath, Frank Wang, Evan Dorundo, Rahul Desai, Tyler Zhu, Samyak Parajuli, Mike Guo, Dawn Song, Jacob Steinhardt, and Justin Gilmer. The many faces of robustness: A critical analysis of out-of-distribution generalization. *ICCV*, 2021. <https://arxiv.org/abs/2006.16241>.

- [65] Dan Hendrycks, Kevin Zhao, Steven Basart, Jacob Steinhardt, and Dawn Song. Natural adversarial examples. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021. <https://arxiv.org/abs/1907.07174>.
- [66] Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. Training compute-optimal large language models, 2022. <https://arxiv.org/abs/2203.15556>.
- [67] Raphael Hoffmann, Congle Zhang, Xiao Ling, Luke Zettlemoyer, and Daniel S Weld. Knowledge-based weak supervision for information extraction of overlapping relations. In *Annual Meeting of the Association for Computational Linguistics (ACL)*, 2011. <https://aclanthology.org/P11-1055>.
- [68] Andrew Hundt, William Agnew, Vicky Zeng, Severin Kacianka, and Matthew Gombolay. Robots enact malignant stereotypes. In *Conference on Fairness, Accountability, and Transparency (FAccT)*, 2022. <https://arxiv.org/abs/2207.11569>.
- [69] Gabriel Ilharco, Mitchell Wortsman, Ross Wightman, Cade Gordon, Nicholas Carlini, Rohan Taori, Achal Dave, Vaishaal Shankar, Hongseok Namkoong, John Miller, Hannaneh Hajishirzi, Ali Farhadi, and Ludwig Schmidt. OpenCLIP, July 2021. <https://doi.org/10.5281/zenodo.5143773>.
- [70] Gabriel Ilharco, Mitchell Wortsman, Samir Yitzhak Gadre, Shuran Song, Hannaneh Hajishirzi, Simon Kornblith, Ali Farhadi, and Ludwig Schmidt. Patching open-vocabulary models by interpolating weights. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022. <https://arxiv.org/abs/2208.05592>.
- [71] Andrew Ilyas, Sung Min Park, Logan Engstrom, Guillaume Leclerc, and Aleksander Madry. Datamodels: Predicting predictions from training data, 2022. <https://arxiv.org/abs/2202.00622>.
- [72] Tanuj Jain, Christopher Lennan, Zubin John, and Dat Tran. Imagededup, 2019. <https://github.com/idealo/imagededup>.
- [73] Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc V Le, Yunhsuan Sung, Zhen Li, and Tom Duerig. Scaling up visual and vision-language representation learning with noisy text supervision. In *International Conference on Machine Learning (ICML)*, 2021. <https://arxiv.org/abs/2102.05918>.
- [74] Mon-Fong Jiang, Shian-Shyong Tseng, and Chih-Ming Su. Two-phase clustering process for outliers detection. *Pattern recognition letters*, 2001. <https://www.sciencedirect.com/science/article/abs/pii/S0167865500001318>.
- [75] Jeff Johnson, Matthijs Douze, and Hervé Jégou. Billion-scale similarity search with GPUs. *IEEE Transactions on Big Data*, 2019. <https://arxiv.org/abs/1702.08734>.
- [76] Justin Johnson, Bharath Hariharan, Laurens van der Maaten, Li Fei-Fei, C. Lawrence Zitnick, and Ross B. Girshick. CLEVR: A diagnostic dataset for compositional language and elementary visual reasoning. *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017. <https://arxiv.org/abs/1612.06890>.
- [77] Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. Bag of tricks for efficient text classification. In *Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, 2017. <https://arxiv.org/abs/1607.01759>.
- [78] Juelich Supercomputing Center. JUWELS Booster Supercomputer, 2020. <https://apps.fz-juelich.de/jsc/hps/juwels/configuration.html#hardware-configuration-of-the-system-name-booster-module>.
- [79] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling laws for neural language models, 2020. <https://arxiv.org/abs/2001.08361>.
- [80] Kimmo Karkkainen and Jungseock Joo. Fairface: Face attribute dataset for balanced race, gender, and age for bias measurement and mitigation. In *IEEE/CVF Winter Conference on Applications of Computer Vision*, 2021. <https://arxiv.org/abs/1908.04913>.

- [81] Pang Wei Koh and Percy Liang. Understanding black-box predictions via influence functions. In *International Conference on Machine Learning (ICML)*, 2017. <https://arxiv.org/abs/1703.04730>.
- [82] Pang Wei Koh, Kai-Siang Ang, Hubert Teo, and Percy S Liang. On the accuracy of influence functions for measuring group effects. *Advances in Neural Information Processing Systems (NeurIPS)*, 2019. <https://arxiv.org/abs/1905.13289>.
- [83] Pang Wei Koh, Shiori Sagawa, Henrik Marklund, Sang Michael Xie, Marvin Zhang, Akshay Balsubramani, Weihua Hu, Michihiro Yasunaga, Richard Lanus Phillips, Irena Gao, Tony Lee, Etienne David, Ian Stavness, Wei Guo, Berton A. Earnshaw, Imran S. Haque, Sara Beery, Jure Leskovec, Anshul Kundaje, Emma Pierson, Sergey Levine, Chelsea Finn, and Percy Liang. WILDS: A benchmark of in-the-wild distribution shifts. In *International Conference on Machine Learning (ICML)*, 2021. <https://arxiv.org/abs/2012.07421>.
- [84] Simon Kornblith, Jonathon Shlens, and Quoc V Le. Do better imagenet models transfer better? In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019. <https://arxiv.org/abs/1805.08974>.
- [85] Jonathan Krause, Michael Stark, Jia Deng, and Li Fei-Fei. 3d object representations for fine-grained categorization. In *International Conference on Computer Vision Workshops (ICML)*, 2013. https://www.cv-foundation.org/openaccess/content_iccv_workshops_2013/W19/html/Krause_3D_Object_Representations_2013_ICCV_paper.html.
- [86] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images, 2009. <https://www.cs.toronto.edu/~kriz/learning-features-2009-TR.pdf>.
- [87] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2012. https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf.
- [88] Ronan Le Bras, Swabha Swayamdipta, Chandra Bhagavatula, Rowan Zellers, Matthew Peters, Ashish Sabharwal, and Yejin Choi. Adversarial filters of dataset biases. In *International Conference on Machine Learning (ICML)*, 2020. <https://arxiv.org/abs/2002.04108>.
- [89] Yann LeCun. The MNIST database of handwritten digits, 1998. <http://yann.lecun.com/exdb/mnist/>.
- [90] Katherine Lee, Daphne Ippolito, Andrew Nystrom, Chiyuan Zhang, Douglas Eck, Chris Callison-Burch, and Nicholas Carlini. Deduplicating training data makes language models better. In *Annual Meeting of the Association for Computational Linguistics (ACL)*, 2021. <https://arxiv.org/abs/2107.06499>.
- [91] Yi Li and Nuno Vasconcelos. Repair: Removing representation bias by dataset resampling. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019. <https://arxiv.org/abs/1904.07911>.
- [92] Yulong Liu, Guibo Zhu, Bin Zhu, Qi Song, Guojing Ge, Haoran Chen, GuanHui Qiao, Ru Peng, Lingxiang Wu, and Jinqiao Wang. Taisu: A 166m large-scale high-quality dataset for chinese vision-language pre-training. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022. https://proceedings.neurips.cc/paper_files/paper/2022/file/6a386d703b50f1cf1f61ab02a15967bb-Paper-Datasets_and_Benchmarks.pdf.
- [93] Zhuang Liu, Hanzi Mao, Chao-Yuan Wu, Christoph Feichtenhofer, Trevor Darrell, and Saining Xie. A convnet for the 2020s. *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022. <https://arxiv.org/abs/2201.03545>.
- [94] Mario Lucic, Matthew Faulkner, Andreas Krause, and Dan Feldman. Training gaussian mixture models at scale via coresets. *Journal of Machine Learning Research (JMLR)*, 2018. <http://jmlr.org/papers/v18/15-506.html>.
- [95] S. Maji, J. Kannala, E. Rahtu, M. Blaschko, and A. Vedaldi. Fine-grained visual classification of aircraft, 2013. <https://arxiv.org/abs/1306.5151>.
- [96] Gideon S Mann and Andrew McCallum. Generalized expectation criteria for semi-supervised learning with weakly labeled data. *Journal of Machine Learning Research (JMLR)*, 2010. <https://www.jmlr.org/papers/v11/mann10a.html>.

- [97] Mark Mazumder, Colby Banbury, Xiaozhe Yao, Bojan Karlaš, William Gaviria Rojas, Sudnya Diamos, Greg Diamos, Lynn He, Douwe Kiela, David Jurado, David Kanter, Rafael Mosquera, Juan Ciro, Lora Aroyo, Bilge Acun, Sabri Eyuboglu, Amirata Ghorbani, Emmett Goodman, Tariq Kane, Christine R. Kirkpatrick, Tzu-Sheng Kuo, Jonas Mueller, Tristan Thrush, Joaquin Vanschoren, Margaret Warren, Adina Williams, Serena Yeung, Newsha Ardalani, Praveen Paritosh, Ce Zhang, James Zou, Carole-Jean Wu, Cody Coleman, Andrew Ng, Peter Mattson, and Vijay Janapa Reddi. Dataperf: Benchmarks for data-centric ai development, 2022. <https://arxiv.org/abs/2207.10062>.
- [98] Baharan Mirzasoleiman, Jeff Bilmes, and Jure Leskovec. Coresets for data-efficient training of machine learning models. In *International Conference on Machine Learning (ICML)*, 2020. <https://arxiv.org/abs/1906.01827>.
- [99] Yuval Netzer, Tao Wang, Adam Coates, Alessandro Bissacco, Bo Wu, and Andrew Y Ng. Reading digits in natural images with unsupervised feature learning. In *Advances in Neural Information Processing Systems (NeurIPS) Workshops*, 2011. <https://storage.googleapis.com/pub-tools-public-publication-data/pdf/37648.pdf>.
- [100] Andrew Ng, Dillon Laird, and Lynn He. Data-centric ai competition, 2021. <https://https-deeplearning-ai.github.io/data-centric-comp/>.
- [101] Thao Nguyen, Gabriel Ilharco, Mitchell Wortsman, Sewoong Oh, and Ludwig Schmidt. Quality not quantity: On the interaction between dataset design and robustness of clip. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022. <https://openreview.net/forum?id=LTCBavFWp5C>.
- [102] Maria-Elena Nilsback and Andrew Zisserman. Automated flower classification over a large number of classes. In *Indian Conference on Computer Vision, Graphics and Image Processing*, 2008. <https://ieeexplore.ieee.org/document/4756141>.
- [103] OpenAI. Gpt-4 technical report, 2023. <https://arxiv.org/abs/2303.08774>.
- [104] Vicente Ordonez, Girish Kulkarni, and Tamara L. Berg. Im2text: Describing images using 1 million captioned photographs. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2011. https://papers.nips.cc/paper_files/paper/2011/file/5dd9db5e033da9c6fb5ba83c7a7ebea9-Paper.pdf.
- [105] Omkar M. Parkhi, Andrea Vedaldi, Andrew Zisserman, and C. V. Jawahar. Cats and dogs. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2012. <https://ieeexplore.ieee.org/document/6248092>.
- [106] Mansheej Paul, Surya Ganguli, and Gintare Karolina Dziugaite. Deep learning on a data diet: Finding important examples early in training. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2021. <https://arxiv.org/abs/2107.07075>.
- [107] Hieu Pham, Zihang Dai, Golnaz Ghiasi, Hanxiao Liu, Adams Wei Yu, Minh-Thang Luong, Mingxing Tan, and Quoc V. Le. Combined scaling for zero-shot transfer learning, 2021. <https://arxiv.org/abs/2111.10050>.
- [108] Vinay Uday Prabhu and Abeba Birhane. Large image datasets: A pyrrhic win for computer vision? In *Winter Conference on Applications of Computer Vision (WACV)*, 2020. <https://arxiv.org/abs/2006.16923>.
- [109] Garima Pruthi, Frederick Liu, Satyen Kale, and Mukund Sundararajan. Estimating training data influence by tracing gradient descent. *Advances in Neural Information Processing Systems (NeurIPS)*, 2020. <https://arxiv.org/abs/2002.08484>.
- [110] Filip Radenovic, Abhimanyu Dubey, Abhishek Kadian, Todor Mihaylov, Simon Vandenhende, Yash Patel, Yi Wen, Vignesh Ramanathan, and Dhruv Mahajan. Filtering, distillation, and hard negatives for vision-language pre-training. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023. <https://arxiv.org/abs/2301.02280>.
- [111] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In *International Conference on Machine Learning (ICML)*, 2021. <https://arxiv.org/abs/2103.00020>.

- [112] Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. Robust speech recognition via large-scale weak supervision, 2022. <https://arxiv.org/abs/2212.04356>.
- [113] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research (JMLR)*, 2020. <https://arxiv.org/abs/1910.10683>.
- [114] Vikram V. Ramaswamy, Sing Yu Lin, Dora Zhao, Aaron B. Adcock, Laurens van der Maaten, Deepti Ghadiyaram, and Olga Russakovsky. Beyond web-scraping: Crowd-sourcing a geodiverse dataset, 2023. <https://arxiv.org/abs/2301.02560>.
- [115] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. In *International Conference on Machine Learning (ICML)*, 2021. <https://arxiv.org/abs/2102.12092>.
- [116] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents, 2022. <https://arxiv.org/abs/2204.06125>.
- [117] A. J. Ratner, B. Hancock, J. Dunnmon, F. Sala, S. Pandey, and C. Ré. Training complex models with multi-task weak supervision. In *Association for the Advancement of Artificial Intelligence (AAAI)*, 2019. <https://arxiv.org/abs/1810.02840>.
- [118] Alexander J Ratner, Christopher M De Sa, Sen Wu, Daniel Selsam, and Christopher Ré. Data programming: Creating large training sets, quickly. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2016. <https://arxiv.org/abs/1605.07723>.
- [119] Alexander J Ratner, Stephen H Bach, Henry Ehrenberg, Jason Fries, Sen Wu, and Christopher Ré. Snorkel: Rapid training data creation with weak supervision. In *Very Large Data Bases Conference (VLDB)*, 2017. <https://arxiv.org/abs/1711.10160>.
- [120] Christopher Ré. Overton: A data system for monitoring and improving machine-learned products. In *10th Conference on Innovative Data Systems Research, CIDR 2020, Amsterdam, The Netherlands, January 12-15, 2020, Online Proceedings*. [www.cidrdb.org](http://cidrdb.org/cidr2020/papers/p33-re-cidr20.pdf), 2020. URL <http://cidrdb.org/cidr2020/papers/p33-re-cidr20.pdf>.
- [121] Benjamin Recht, Rebecca Roelofs, Ludwig Schmidt, and Vaishaal Shankar. Do ImageNet classifiers generalize to ImageNet? In *International Conference on Machine Learning (ICML)*, 2019. <http://proceedings.mlr.press/v97/recht19a.html>.
- [122] William A Gviria Rojas, Sudnya Diamos, Keertan Ranjan Kini, David Kanter, Vijay Janapa Reddi, and Cody Coleman. The dollar street dataset: Images representing the geographic and socioeconomic diversity of the world. In *Advances in Neural Information Processing Systems (NeurIPS) Datasets and Benchmarks Track*, 2022. <https://openreview.net/forum?id=qnfYsave0U4>.
- [123] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022. <https://arxiv.org/abs/2112.10752>.
- [124] Peter J Rousseeuw and Mia Hubert. Robust statistics for outlier detection. *Wiley interdisciplinary reviews: Data mining and knowledge discovery*, 2011. <http://i2pc.es/coss/Docencia/SignalProcessingReviews/Rousseeuw2011.pdf>.
- [125] Peter J Rousseeuw and Mia Hubert. Anomaly detection by robust statistics. *Wiley interdisciplinary reviews: Data mining and knowledge discovery*, 2018. <https://wires.onlinelibrary.wiley.com/doi/pdf/10.1002/widm.1236>.
- [126] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 2015. <https://arxiv.org/abs/1409.0575>.
- [127] Shiori Sagawa, Pang Wei Koh, Tony Lee, Irena Gao, Sang Michael Xie, Kendrick Shen, Ananya Kumar, Weihua Hu, Michihiro Yasunaga, Henrik Marklund, Sara Beery, Etienne David, Ian Stavness, Wei Guo, Jure Leskovec, Kate Saenko, Tatsunori Hashimoto, Sergey Levine, Chelsea Finn, and Percy Liang. Extending the wilds benchmark for unsupervised

- adaptation. In *International Conference on Learning Representations (ICLR)*, 2022. <https://arxiv.org/abs/2112.05090>.
- [128] Christoph Schuhmann, Richard Vencu, Romain Beaumont, Robert Kaczmarczyk, Clayton Mullis, Aarush Katta, Theo Coombes, Jenia Jitsev, and Aran Komatsuzaki. LAION-400M: Open dataset of clip-filtered 400 million image-text pairs, 2021. <https://arxiv.org/abs/2111.02114>.
- [129] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade W Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, Patrick Schramowski, Srivatsa R Kundurthy, Katherine Crowson, Ludwig Schmidt, Robert Kaczmarczyk, and Jenia Jitsev. LAION-5B: An open large-scale dataset for training next generation image-text models. In *Thirty-sixth Conference on Neural Information Processing Systems (NeurIPS), Datasets and Benchmarks Track*, 2022. <https://openreview.net/forum?id=M3Y74vmsMcY>.
- [130] Ozan Sener and Silvio Savarese. Active learning for convolutional neural networks: A core-set approach. In *International Conference on Learning Representations (ICLR)*, 2018. <https://openreview.net/forum?id=H1aIuk-RW>.
- [131] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *Annual Meeting of the Association for Computational Linguistics (ACL)*, 2018. <https://aclanthology.org/P18-1238/>.
- [132] Sheng Shen, Liunian Harold Li, Hao Tan, Mohit Bansal, Anna Rohrbach, Kai-Wei Chang, Zhewei Yao, and Kurt Keutzer. How much can clip benefit vision-and-language tasks?, 2021. <https://arxiv.org/abs/2107.06383>.
- [133] Changho Shin, Winfred Li, Harit Vishwakarma, Nicholas Roberts, and Frederic Sala. Universalizing weak supervision. In *International Conference on Learning Representations (ICLR)*, 2022. <https://openreview.net/forum?id=YpPiNigTzMT>.
- [134] Haoyu Song, Li Dong, Weinan Zhang, Ting Liu, and Furu Wei. CLIP models are few-shot learners: Empirical studies on VQA and visual entailment. In *Annual Meeting of the Association for Computational Linguistics (ACL)*, 2022. <https://aclanthology.org/2022.acl-long.421>.
- [135] Ben Sorscher, Robert Geirhos, Shashank Shekhar, Surya Ganguli, and Ari S. Morcos. Beyond neural scaling laws: beating power law scaling via data pruning. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022. <https://openreview.net/forum?id=UmvS1P-PyV>.
- [136] Krishna Srinivasan, Karthik Raman, Jiecao Chen, Michael Bendersky, and Marc Najork. Wit: Wikipedia-based image text dataset for multimodal multilingual machine learning. In *44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2021. <https://arxiv.org/abs/2103.01913>.
- [137] Johannes Stalldkamp, Marc Schlipfing, Jan Salmen, and Christian Igel. The german traffic sign recognition benchmark: a multi-class classification competition. In *International Joint Conference on Neural Networks (IJCNN)*, 2011. <https://ieeexplore.ieee.org/document/6033395>.
- [138] Swabha Swayamdipta, Roy Schwartz, Nicholas Lourie, Yizhong Wang, Hannaneh Hajishirzi, Noah A. Smith, and Yejin Choi. Dataset cartography: Mapping and diagnosing datasets with training dynamics. In *Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2020. <https://aclanthology.org/2020.emnlp-main.746>.
- [139] Rohan Taori, Achal Dave, Vaishaal Shankar, Nicholas Carlini, Benjamin Recht, and Ludwig Schmidt. Measuring robustness to natural distribution shifts in image classification. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2020. <https://dl.acm.org/doi/abs/10.5555/3495724.3497285>.
- [140] Bart Thomee, David A Shamma, Gerald Friedland, Benjamin Elizalde, Karl Ni, Douglas Poland, Damian Borth, and Li-Jia Li. YFCC100M: The new data in multimedia research. *Communications of the ACM*, 2016. <https://arxiv.org/abs/1503.01817>.

- [141] Mariya Toneva, Alessandro Sordoni, Remi Tachet des Combes, Adam Trischler, Yoshua Bengio, and Geoffrey J Gordon. An empirical study of example forgetting during deep neural network learning. In *International Conference on Learning Representations (ICLR)*, 2018. <https://arxiv.org/abs/1812.05159>.
- [142] Bastiaan S Veeling, Jasper Linmans, Jim Winkens, Taco Cohen, and Max Welling. Rotation equivariant CNNs for digital pathology, 2018. <https://arxiv.org/abs/1806.03962>.
- [143] Haohan Wang, Songwei Ge, Zachary Lipton, and Eric P Xing. Learning robust global representations by penalizing local predictive power. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2019. <https://arxiv.org/abs/1905.13549>.
- [144] Ryan Webster, Julien Rabin, Loic Simon, and Frederic Jurie. On the de-duplication of laion-2b, 2023. <https://arxiv.org/abs/2303.12733>.
- [145] Kai Wei, Rishabh Iyer, and Jeff Bilmes. Submodularity in data subset selection and active learning. In *International Conference on Machine Learning (ICML)*, 2015. <https://proceedings.mlr.press/v37/wei15.html>.
- [146] Jianxiong Xiao, Krista A Ehinger, James Hays, Antonio Torralba, and Aude Oliva. Sun database: Exploring a large collection of scene categories. *International Journal of Computer Vision (IJCV)*, 2016. <https://link.springer.com/article/10.1007/s11263-014-0748-y>.
- [147] Kaiyu Yang, Klint Qinami, Li Fei-Fei, Jia Deng, and Olga Russakovsky. Towards fairer datasets: filtering and balancing the distribution of the people subtree in the imagenet hierarchy. In *Conference on Fairness, Accountability, and Transparency (FAccT)*, 2020. <https://arxiv.org/abs/1912.07726>.
- [148] Kaiyu Yang, Jacqueline H Yau, Li Fei-Fei, Jia Deng, and Olga Russakovsky. A study of face obfuscation in ImageNet. In *International Conference on Machine Learning (ICML)*, 2022. <https://arxiv.org/abs/2103.06191>.
- [149] Lewei Yao, Runhui Huang, Lu Hou, Guansong Lu, Minzhe Niu, Hang Xu, Xiaodan Liang, Zhenguo Li, Xin Jiang, and Chunjing Xu. Filip: Fine-grained interactive language-image pre-training. In *International Conference on Learning Representations (ICLR)*, 2022. <https://arxiv.org/abs/2111.07783>.
- [150] Shuhei Yokoo. Contrastive learning with large memory bank and negative embedding subtraction for accurate copy detection, 2021. <https://arxiv.org/abs/2112.04323>.
- [151] Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. *Transactions of the Association for Computational Linguistics*, 2014. <https://aclanthology.org/Q14-1006/>.
- [152] Dantong Yu, Gholamhosein Sheikholeslami, and Aidong Zhang. Findout: Finding outliers in very large datasets. *Knowledge and information Systems*, 2002. <https://link.springer.com/article/10.1007/s101150200013>.
- [153] Lu Yuan, Dongdong Chen, Yi-Ling Chen, Noel Codella, Xiyang Dai, Jianfeng Gao, Houdong Hu, Xuedong Huang, Boxin Li, Chunyuan Li, et al. Florence: A new foundation model for computer vision, 2021. <https://arxiv.org/abs/2111.11432>.
- [154] Man-Ching Yuen, Irwin King, and Kwong-Sak Leung. A survey of crowdsourcing systems. In *SocialCom. IEEE*, 2011. <https://ieeexplore.ieee.org/document/6113213>.
- [155] Matei Zaharia, Reynold S Xin, Patrick Wendell, Tathagata Das, Michael Armbrust, Ankur Dave, Xiangrui Meng, Josh Rosen, Shivaram Venkataraman, Michael J Franklin, et al. Apache spark: a unified engine for big data processing. *Communications of the ACM*, 2016. <https://dl.acm.org/doi/10.1145/2934664>.
- [156] Xiaohua Zhai, Joan Puigcerver, Alexander Kolesnikov, Pierre Ruysen, Carlos Riquelme, Mario Lucic, Josip Djolonga, André Susano Pinto, Maxim Neumann, Alexey Dosovitskiy, Lucas Beyer, Olivier Bachem, Michael Tschannen, Marcin Michalski, Olivier Bousquet, Sylvain Gelly, and Neil Houlsby. The visual task adaptation benchmark, 2019. <http://arxiv.org/abs/1910.04867>.

- [157] Jieyu Zhang, Yue Yu, Yinghao Li, Yujing Wang, Yaming Yang, Mao Yang, and Alexander Ratner. WRENCH: A comprehensive benchmark for weak supervision. In *NeurIPS*, 2021. URL <https://openreview.net/forum?id=Q9SKS5k8io>.
- [158] Jieyu Zhang, Cheng-Yu Hsieh, Yue Yu, Chao Zhang, and Alexander Ratner. A survey on programmatic weak supervision, 2022. <https://arxiv.org/abs/2202.05433>.
- [159] Zhifei Zhang, Yang Song, and Hairong Qi. Age progression/regression by conditional adversarial autoencoder. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017. <https://arxiv.org/abs/1702.08423>.
- [160] Xingyi Zhou, Rohit Girdhar, Armand Joulin, Philipp Krähenbühl, and Ishan Misra. Detecting twenty-thousand classes using image-level supervision. In *European Conference on Computer Vision (ECCV)*, 2022. <https://arxiv.org/abs/2201.02605>.