Active Data Curation Effectively Distills Large-Scale Multimodal Models

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Abstract

Knowledge distillation (KD) is the de facto standard for compressing large-scale multimodal models into smaller ones. Prior works have explored ever more complex KD strategies involving different objectives, teacher-ensembles, and weight inheritance. In this work, we explore an alternative, yet simple approach—active data curation as effective distillation for contrastive multimodal pretraining. Our simple online batch selection method, ACID, outperforms strong KD baselines across various model-, data- and compute-configurations. Further, we find such an active curation strategy to in fact be complementary to standard KD, and can be effectively combined to train highly performant inference-efficient models. Our simple and scalable pretraining framework, ACED, achieves state-of-the-art results across 27 zero-shot classification and image-text retrieval tasks with upto 11% less inference FLOPs. We further demonstrate that ACED yields strong vision-encoders for training generative multimodal models, outperforming larger vision encoders on image-captioning and visual question-answering tasks.

1. Introduction

Deploying multimodal foundation models [14] like CLIP [119] on edge devices is challenging due to their high inference costs and memory footprints. This motivates the need for compressing these foundation models into smaller ones that can be efficiently deployed for cheaper and faster inference, while retaining the performance of their larger counterparts. *Knowledge distillation (KD)* [65] is a classic model compression technique—a method for transferring knowledge from a large-scale "teacher" model into a smaller "student" model, via matching the student and teacher logits, features or activations. KD has been extensively deployed for creating small, performant models like Gemma-2 [148], Phi-3 [4], Gemini-1.5 Flash [126], and SD3-Turbo [136].

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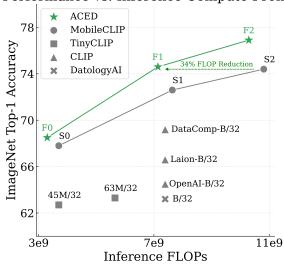
Figure 1. **Performance-Inference Frontier.** Our *ACED* models (**A**ctive **C**uration with **E**xplicit **D**istillation, see Sec. 3), achieve a new pareto frontier for performance (measured by ImageNet top-1 zero-shot validation accuracy) vs. inference GFLOPs.

Here, our primary goal is to downscale contrastive vision-language models such as CLIP [119] and SigLIP [190]), without compromising downstream performance. Prior works in this domain focus on complex KD strategies as the key solution—the current SoTA (TinyCLIP [173] and MobileCLIP [155]) use extensive combinations of methods such as strong data-augmentation policies, multi-teacher ensembles, synthetic captions, complicated weight-inheritance, pruning strategies, and bespoke model architectures.

In this work, we take an alternative simplifying approach— we propose to use *active data curation as an effective strategy for distilling large vision-language models (VLMs)* into smaller and more FLOP-efficient multimodal models.

Our method, *ACID* (**A**ctive **C**uration as **I**mplicit **D**istillation), automatically selects samples that reduce the performance gap between a small model being trained (*student*) and a larger frozen model (*reference*). Under appropriate conditions, we find this to be an effective alternative to

standard KD for distilling knowledge to small models. To the best of our knowledge, this is a novel and surprising finding since prior work in data curation assumed that larger models could not be used to select data for smaller ones as the *capacity gap* between the two could prove inhibitory [48, 107]. Through a novel theoretical interpretation and extensive experiments, instead, we demonstrate that *ACID* is not only effective but actually improves over KD, exhibiting more favourable scaling with respect to training compute. We also conduct careful ablation studies uncovering critical factors influencing the quality of the trained student model, including, reference model capacity and training dataset.

After comprehensively demonstrating the effectiveness of data curation as an alternative to KD , we further show how the two can be profitably combined to further improve performance. This suggests that the *information distilled to the smaller model through each approach is complementary*.

Finally, we incorporate our findings to develop a simple yet extremely effective pretraining recipe, *ACED* (ACID with Explicit Distillation), to train FLOP-efficient image-text contrastive models. Our method, absent bespoke components such as efficient architectures or data-augmentations, outperforms SoTA CLIP and SigLIP models with greater FLOP-efficiency at inference-time and shows a significant improvement over 27 downstream tasks against the previous SoTA for FLOP-efficient models [155, 173]. We further demonstrate that our *ACED* vision-encoders provide strong backbones for generative multimodal models, outperforming larger and FLOP-inefficient vision-encoders on image-captioning and visual-question-answering (VQA) tasks.

2. Related Work

Multimodal Data Curation. Recent works have emphasised the importance of data quality for pretraining multimodal models [41, 48, 106, 109, 153]. Specifically, it has been shown that offline curation of noisy web-scale data can result in large pretraining efficiency gains [1, 2, 19, 20, 42, 69, 75, 101, 103, 138, 144, 159, 160, 167–169, 178, 186].

However, such static offline curation methods that pre-filter data do not take into account the training dynamics of the current learner model, and hence can suffer at larger scales [53]. As a result, there have been many recent attempts to introduce *online batch selection* criteria that account for the current state of the learner (*e.g.*, at each step select training samples that have the largest learner loss) [67, 70, 73, 100, 137, 143, 170, 177, 197]. Going further, Mindermann et al. [107] introduced the RHO-Loss that considers both current learner state and a pretrained data-selector (reference) model. This criterion has since been used in many efforts to improve the efficiency of foundation model pretraining [17, 31, 34, 35, 39, 66]. As these methods seek to improve pretraining efficiency, the pretrained reference

models that are used as *data selectors are typically smaller than the learner models they are used to train* [34, 35, 42]. In fact, Fang et al. [42], Gadre et al. [48], Yu et al. [186] all showed that increasing reference model size can potentially hurt learner model performance. Our work tells a different story, finding that *large data selectors can effectively curate data for inference-time FLOP-efficient learner models*.

Knowledge Distillation. First introduced by Buciluǎ et al. [18] and further popularized by Ba and Caruana [7], Hinton [65], knowledge distillation (KD) is a classic technique for transferring knowledge from a larger model (*teacher*) to another smaller one (*student*), by optimizing the student to match certain outputs (logits, features, intermediate activations *etc.*) of the teacher model. It has been extensively used for compressing large models into smaller, deployable ones in unimodal tasks like image-classification [12, 25, 113, 149, 158, 165] and language representation learning [5, 55, 76, 95, 134, 146, 179]. Further works have extended KD to use teacher-ensembles [21, 37, 105, 135, 141, 145, 185, 200], and different distillation training objectives [68, 92, 122, 147, 151, 175, 196].

Most relevant to our work are KD methods in the mutlimodal regime, which is an underexplored area. Nevertheless, there are a number of recent efforts to distill strong but efficient CLIP models. Sameni et al. [133] introduced SF-CLIP, a method using masked distillation, while Vasu et al. [155] proposed MobileCLIP, exploring downscaling CLIP models for mobile-deployment by using multi-teacher contrastive-KD, synthetic captions, and data-augmentations. Wu et al. [173] further proposed TinyCLIP—a weight inheritance method combined with an affinity-mimicking strategy to yield tiny CLIP models. Yang et al. [180] conducted an empirical study (CLIP-KD) on different objective functions for effectively distilling CLIP models, across different scales. Finally, CLIP-CID [183] uses an image semantic balancing strategy coupled with cluster-instance discrimination for better teacher-to-student knowledge transfer during the KD process. We compare against all of these methods in our experimental results in Sec. 4.

Accelerating Knowledge Distillation There has been some prior work attempting to make KD-based pretraining more efficient [140, 142, 188]. Some works have investigated accelerating vanilla KD using active learning in small-scale classification tasks [83, 163, 176]. However, these approaches require a costly iterative process, involving synthetic generation, followed by active sample selection to produce pseudo-labels from a teacher model, thereby limiting their scalability. Another line of work has studied data-selection methods for improving KD, typically using uncertainty-based data, logit and feature selection [59, 90, 97, 123, 130, 161, 162, 172, 199], contextual retrieval and sample augmentation from a large data pool [50, 71, 94, 98, 118, 191], or influence-function based

sample selection [83, 184]. Contrary to these works, Beyer et al. [12] and Hao et al. [57] suggest that vanilla knowledge distillation is optimal in "infinite-data regimes".

Surprisingly, all these prior works operate primarily in the unimodal image/text classification regime, and none have been scaled to multimodal foundation model training. We showcase, for the first time, that *simple data selection using online batch selection outperforms standard KD for pretraining multimodal models*. We further study the optimal strategies for combining vanilla KD and active data curation in order to best leverage their complementary strengths.

3. Methods

3.1. Preliminaries

Contrastive Vision-Language Pretraining. We follow standard multimodal pretraining frameworks like CLIP [119] and SigLIP [190]. We assume a large pretraining dataset $\mathcal{D}$, containing image-text pairs. Our goal is to train a two-tower VLM with parameters θ whose image-encoder f^{img} and text-encoder f^{txt} are initialized from scratch. At each training step, we sample a mini-batch, $\mathcal{B}=\{x_1,\ldots,x_b\}$, where $x_i = (I_i, T_i)$ denotes the ith image-text pair in the mini-batch and b denotes the batch-size. We then encode and normalize the embeddings of each image-text pair in the mini-batch as $z_i^{\text{img}}=\frac{f^{\text{img}}(I_i|\theta)}{\|f^{\text{img}}(I_i|\theta)\|_2}$ and $z_i^{\text{txt}}=\frac{f^{\text{txt}}(T_i|\theta)}{\|f^{\text{txt}}(T_i|\theta)\|_2}$. The pairwise similarities $l_{ij}(\theta) = \alpha z_i^{\text{img}} \cdot z_j^{\text{txt}} + \beta$, where α, β are learnable inverse-temperature and offset hyperparameters, can be converted into pairwise probabilities with a row- or column-wise softmax as follows,

$$p_{ij}^{\text{img}\to\text{txt}} = \exp(l_{ij}) / \sum_{k=1}^{b} \exp(l_{ik}) \qquad (1)$$

$$p_{ij}^{\text{txt}\to\text{img}} = \exp(l_{ij}) / \sum_{k=1}^{b} \exp(l_{ki}) \qquad (2)$$

or $p_{ij}^{\text{sig}} = \sigma(l_{ij})$ with a sigmoid operation. The contrastive image-text losses seek to align embeddings of paired images and texts $(z_i^{\text{img}}, z_i^{\text{txt}})$, while pushing apart embeddings of mismatched images and texts $(z_i^{\text{img}}, z_{j\neq i}^{\text{txt}})$. There are two widely used contrastive variants i.e., $\mathcal{L}_{\text{softmax}}$ for CLIP [119] and $\mathcal{L}_{\text{sigmoid}}$ for SigLIP [190], both of which can be framed as $\mathcal{L}(x_i;\mathcal{B})=-\sum_{j=1}^{b} y_j(x_i) \log p_{ij}=\text{CE}[y(x_i); p(x_i)]$ for a suitable choice of binary labels y and probabilities p, where CE is the standard cross-entropy loss (see supplementary for details). By default, we use the sigmoid variant as it is more scalable, but also run ablations with the softmax variant.

Contrastive Distillation. Given the student θ and a pretrained teacher model θ_{teacher}, our aim is to distill the contrastive logit matrix from teacher to student. Formally, given a data-batch $\mathcal{B}$, we extract teacher embeddings

$(z_i^{\text{img}}, z_i^{\text{txt}})(\theta_{\text{teacher}})$ and student embeddings $(z_i^{\text{img}}, z_i^{\text{txt}})(\theta)$, yielding pairwise similarities $l_{ij}(\theta_{\text{teacher}})$ and $l_{ij}(\theta)$ for the teacher and student respectively. Let p and q be the pairwise probabilities induced by teacher and student similarities (Eqs. (1) and (2)). Our knowledge distillation (KD) objective is simply the cross-entropy loss between these distributions:

$$\mathcal{L}_{\text{dist}}(x_i;\mathcal{B}) = \text{KD}[p(x_i), q(x_i)] =$$
$$-\frac{1}{2}\sum_{j=1}^{b} \left(p_{i,j}^{\text{img}\to\text{txt}} \log q_{i,j}^{\text{img}\to\text{txt}} + p_{i,j}^{\text{txt}\to\text{img}} \log q_{i,j}^{\text{txt}\to\text{img}} \right)$$
$$(3)$$

which has previously been explored in unimodal [45, 181] and multimodal contexts [183].

3.2. *ACID*: <u>A</u>ctive <u>C</u>uration as <u>I</u>mplicit <u>D</u>istillation

Setup. We refer to the small model we aim to train as the *student* model, with parameters θ. Given an image-text pretraining dataset $\mathcal{D}$, the straightforward training approach is to sample uniformly random batches of data $\mathcal{B}$ (of size b), from $\mathcal{D}$ at each step t, and minimize $\mathcal{L} \in \{\mathcal{L}_{\text{softmax}}, \mathcal{L}_{\text{sigmoid}}\}$. We refer to this baseline strategy, minimizing $\hat{\mathcal{L}} = \frac{1}{b}\sum_{x_i \sim \mathcal{U}[\mathcal{D}]} \mathcal{L}(x_i; \mathcal{B})$ as the *IID-baseline* (θ_{IID})

Active Data Curation employs a smarter way to select batches, using a pretrained *reference* model θ_{ref}. At each step t, we select a sub-batch $\mathcal{B}$ (size b) from a much larger superbatch $\mathcal{S}$ (size B) according to an *active selection distribution* $\mathcal{A}[\mathcal{S}]$. We use two main criteria for scoring sub-batches $\mathcal{B}$, following prior work in prioritized sampling [34, 107].
1. *Easy-reference scoring* uses the loss-values of the reference θ_{ref} to preferentially sample batches that are easy for θ_{ref}: $s^{\text{easy\_ref}}(\mathcal{B}|\theta_{\text{ref}})=-\mathcal{L}(\mathcal{B}|\theta_{\text{ref}})$.
2. *Learnability scoring* uses the difference in loss-values of the current student θ and the reference θ_{ref} to give high scores to *learnable batches* i.e., batches that are easy for the reference but difficult for the current student: $s^{\text{learn}}(\mathcal{B}|\theta, \theta_{\text{ref}})=\mathcal{L}(\mathcal{B}|\theta)-\mathcal{L}(\mathcal{B}|\theta_{\text{ref}})$.

Prior model-based online batch curation methods used reference models that were *of the same size or smaller* than the model being trained. This was because of (1) *training efficiency*: since data-selection was originally used to reduce training set sizes, reference models were chosen to be small so as to reduce compute overhead, and (2) *unlearnable prioritization*: intuitively, samples that are easily learned (and thus prioritized) by a high-capacity reference might be unlearnable for the lower-capacity learner. Indeed Mindermann et al. [107] observed little effect when increasing reference model capacity, a key limitation of their original method.

<u>A</u>ctive <u>D</u>ata <u>C</u>uration as <u>I</u>mplicit <u>D</u>istillation (ACID). We now show formally that active curation can be cast as "implicit distillation" and should benefit from larger reference models. The model now minimizes $\hat{\mathcal{L}} =$
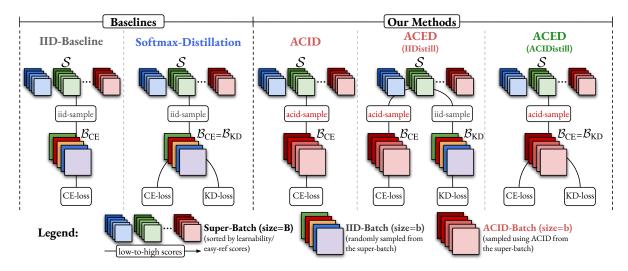
Figure 2. **Different Method Configurations.** We depict all the different method configurations that we consider in our work. Each method can be independently recovered from the unified objective $\mathcal{L}_{\text{full}}$ in Sec. 3.3. The `iid-sample` and `acid-sample` boxes denote the IID-sampling and our *ACID* online batch-selection sampling schemes respectively. For more details, refer to Sec. 3.

$\frac{1}{b}\sum_{x_i\sim\mathcal{A}[\mathcal{S}]}\mathcal{L}(x_i;\mathcal{B})$, which in expectation is $\mathcal{E} = \mathbb{E}[\hat{\mathcal{L}}] = \sum_{x\in\mathcal{D}} a(x)\mathcal{L}(x;\mathcal{B})$ given that super-batches $\mathcal{S}$ are sampled uniformly. Recall that $\mathcal{L}(x;\mathcal{B}) = -\sum_{i=1}^{b} y_i(x)\log q_i(x)$, where y_i are the labels of the contrastive task and q_i are the probabilities induced by the pairwise similarities of the student θ. Let p_i be the probabilities induced by the reference model θ_{ref}. In the case of *easy-reference scoring* and the softmax loss, $a(x) = \frac{1}{Z}\exp\sum_{i=1}^{b} y_i(x)\log p_i(x) = \frac{1}{Z}p_{i^*}(x)$ where i^* is the index of the one-hot label $y(x)$. We derive the following equality (see supplementary for details),

$$\mathcal{E}_{\text{easy-ref}} = \frac{1}{Z}\sum_{x\in\mathcal{D}} \text{KD}[p(x)\cdot y(x); q(x)]. \quad (4)$$

This demonstrates that by curating data according to the reference model θ_{ref}, we implicitly distill its knowledge via a novel data-driven objective, using a combination of model predictions and real labels as targets. Model predictions and real labels have independent sources of noise: false labels can occur due to human error, whereas models may underfit due to biases in training or architecture. As a result, retaining targets where the reference model and labels agree allows for mutual denoising of model predictions and data labels.

Moreover, this suggests that in contrast to the standard active learning paradigm, in which reference models are similarly-sized or smaller than the student model [34, 107], *ACID* should instead benefit from pretrained reference models θ_{ref} that are *larger* than the student model θ for scoring. While counter-intuitive from an active learning perspective, this configuration is natural given our new perspective of active data curation as an implicit form of distillation.

Learnability-based Data Curation is Hard Distillation. When using learnability-based prioritization, the active selection distribution $\mathcal{A}$ factorizes as $a^{\text{learn}} = \frac{1}{Z}\exp(s^{\text{learn}}) =$ $\frac{1}{Z}\exp[\mathcal{L}(\cdot|\theta) - \mathcal{L}(\cdot|\theta_{\text{ref}})] = a^{\text{easy-ref}}\cdot a^{\text{hard-learn}}$ where $a^{\text{hard-learn}} = \frac{1}{Z}\exp[\mathcal{L}(\cdot|\theta)]$ prioritizes examples with high loss according to the student. Since easy-reference prioritization yields implicit distillation (*I-ACID*, Eq. (4)), learnability prioritization yields

$$\mathcal{E}_{\text{learn}} = \frac{1}{Z}\sum_{x\in\mathcal{D}} a^{\text{hard-learn}}(x)\text{KD}[p(x)\cdot y(x); q(x)] \quad (5)$$

i.e. implicit distillation on hard examples ("*H-ACID*") according to the student (see supplementary for details). Prioritizing high-loss examples has been shown to reliably accelerate learning in settings where targets are high-quality [100], as is the case with the combined targets in our ACID.

Joint Batch Sampling. Implementing our ACID method requires sampling examples x from $\mathcal{A}[\mathcal{S}]$ where $a(x|\mathcal{B})=\exp(-\mathcal{L}(x|\mathcal{B}, \theta_{\text{ref}}))$ for ACID or $a(x|\mathcal{B}) = \exp(\mathcal{L}(x|\mathcal{B}, \theta) - \mathcal{L}(x|\mathcal{B}, \theta_{\text{ref}}))$ for Hard-ACID. As such, sampling from $\mathcal{A}[\mathcal{S}]$ requires *jointly selecting examples in a batch*. Following Evans et al. [35] we utilise an iterative approach which incrementally populates the batch conditioned on already-sampled examples. Specifically, this algorithm uses n iterations of a blocked Gibbs sampling approach. Given a subset of data-samples $\mathcal{B}_i$ at iteration i, we compute the conditional batch-scores of all other candidate samples in the super-batch that have not yet been added to the mini-batch $\mathcal{B}_i$, $s^{\text{easy-ref}}(\{\mathcal{B}_i, x\})/s^{\text{learn}}(\{\mathcal{B}_i, x\})\forall x\in\mathcal{S}-\mathcal{B}_i$, then sample a chunk $\{x_k\}$ of size $\frac{b}{n}$ according to these scores independently, and append to the constructed mini-batch, $\mathcal{B}_{i+1}=\mathcal{B}_i\cup\{x_k\}$. The first chunk $\mathcal{B}_1$ is sampled using the independent scores $s^{\text{easy-ref}}(\{x\})/s^{\text{learn}}(\{x\})$. The final sampled mini-batch is yielded after n iterations, $\mathcal{B}=\mathcal{B}_n$ (see Evans et al. [35] for more details). Note that the ratio of the super-batch size and the mini-batch size determines how

aggressively our data selection method filters out samples from the super-batch—we quantify this with the filtering ratio, $f = 1 - \frac{b}{B}$. The larger the filtering ratio f, the stronger is the data selection process at each training step.

Method	λ	$\mathcal{B}_{\text{CE}}$	$\mathcal{B}_{\text{KD}}$	Effective Batch-Size per Iteration
IID-Baseline	$=0$	IID	—	b
Softmax-KD	>0	IID	IID	b
I-ACID	$=0$	*I-ACID*	—	b
H-ACID	$=0$	*H-ACID*	—	b
ACED-IIDistill	>0	*H-ACID*	IID	$2b$
ACED-ACIDistill	>0	*H-ACID*	*H-ACID*	b

Table 1. **Method Instantiations.** We recover different method configurations from our unified objective (see Sec. 3.3), by specifying the data-selection strategies across different batches as well as hyperparameter values. We further indicate the effective mini-batch size per-iteration used by each method for training, and colour-code the different methods for easy referencing from Sec. 4.

3.3. *ACED*: <u>A</u>ctive <u>C</u>uration & <u>E</u>xplicit <u>D</u>istillation

Towards explicit knowledge-transfer. ACID introduces an active curation strategy without using any auxiliary objective beyond the contrastive loss. This induces an implicit form of knowledge transfer from the larger reference model to the small student model. To augment this implicit transfer with an explicit distillation objective, we propose *ACED*, <u>AC</u>ID with <u>E</u>xplicit <u>D</u>isillation, which effectively combines ACID with a softmax contrastive distillation loss (see Eq. (3)).

A unified objective. We now propose a general loss formulation that can flexibly model different instantiations of all our training methods (*IID-Baseline*, *ACID*, *ACED*, and *Softmax-KD*) under one unified objective. At each step t, we first sample the super-batch $\mathcal{S}$ based on the required final mini-batch size b and filtering ratio f (super-batch size is $B = \frac{b}{1-f}$). We then sample two mini-batches from $\mathcal{S}$—the data mini-batch used for training the contrastive loss ($\mathcal{B}_{\text{CE}}$) and the mini-batch used for distillation ($\mathcal{B}_{\text{KD}}$). The two mini-batches can either be sampled using our *ACID* sampling scheme or random IID sampling. Our overall objective is written as, $\mathcal{L}_{\text{full}} = \mathcal{L}_{\text{softmax/sigmoid}}[\mathcal{B}_{\text{CE}}] + \lambda \cdot \mathcal{L}_{\text{dist}}[\mathcal{B}_{\text{KD}}]$.

Tab. 1 and Fig. 2 depict how we can instantiate $\mathcal{L}_{\text{full}}$ to recover different methods and baselines—we colour-code different methods to enable easy cross-referencing later from Sec. 4. Our *IID-Baseline* only uses the contrastive loss trained on an IID-sampled batch. Our implicit distillation methods ({*I/H*}-*ACID*) also use only the contrastive loss but train on actively selected data-batches. For *Softmax-KD*, we only sample an IID batch and use that same batch for both contrastive and distillation losses ($\mathcal{B}_{\text{CE}} = \mathcal{B}_{\text{dist}}$). For our combined *ACED* method, we have two schemes—(1) *ACIDistill* which samples a single mini-batch from $\mathcal{S}$ using *H-ACID*, using that for both contrastive and distillation training ($\mathcal{B}_{\text{CE}} = \mathcal{B}_{\text{KD}}$), and (2) *IIDistill* which samples $\mathcal{B}_{\text{CE}}$ using *H-ACID* and $\mathcal{B}_{\text{KD}}$ using IID sampling. For both *ACED*
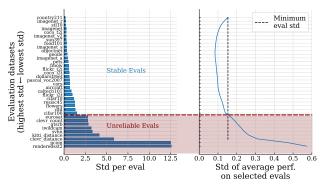

Figure 3. **StableEval: a reliable set of multimodal evaluations.** (*left*) Variability across random pretraining seeds of individual evaluations. (*right*) Variability of average performance across incrementally larger sets of evaluations, starting from the most reliable.

methods, we only use the *H-ACID* sampling scheme as empirically it is more performant than *I-ACID* (see Fig. 4).

4. Experiments

4.1. Implementation Details

Model Architecture and Sizes. Unless otherwise specified, we use standard ViT-S [33] and BERT-small [32] models as our student image-text encoders (typically used by `open_clip`). For some student ablations, we also use (ViT-Ti image, Ti text) and (ViT-B image, B text) configurations. For our reference and teacher models, we conduct a sweep over different sizes—(ViT-Ti, Ti), (ViT-S, S), (ViT-B, B), (ViT-L, L), (ViT-H, H), and (ViT-g, g) for (image, text) encoders respectively. We pretrain all our models (θ_{teacher}, θ_{ref}, θ) from scratch. For more details, refer to supplementary.

Pretraining Datasets. We use the popular DataComp-1B [48] dataset for pretraining all our student models. For training our reference and teacher models, we sweep over four different datasets—WebLI-curated++ [35], WebLI-1B [24], LAION-400M [138], and DataComp-1B [48].

Evaluation Protocol: StableEval. We evaluate our models on a diverse set of benchmarks including zero-shot classification and image-text retrieval datasets following prior multimodal pretraining work [48, 84, 178]. However, many works select non-standardized sets of evaluations and fail to sufficiently justify the reliability of the evaluations they use. To rigorously define an evaluation suite, we collate a standard list of 34 candidate evaluations and conduct a systematic analysis of their reliability. By repeating the same canonical pretraining run multiple times (*e.g.*, CLIP pretraining on DataComp with the *exact same data ordering*, see supplementary for details), we evaluate the variability of each metric across random seeds. In Fig. 3 (left), we find an extreme range in variability across evaluations (stds from
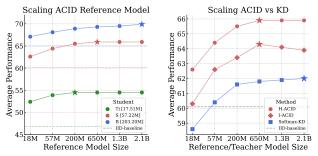
Figure 4. Scaling behaviour of *ACID*. *(left)* We scale up the reference model used for training each student (Ti, S and B) with *H-ACID*—there is an optimal scaling relationship (best reference for each student marked with ⋆) between student and reference sizes. *(right)* Our *H-ACID* and *I-ACID* comprehensively outperform *Softmax-KD* across all teacher scales. Importantly, our *ACID*s outperform the IID baseline even for tiny reference models, whereas *Softmax-KD* struggles to improve over IID with smaller teachers.

0.15% to 12.5%) which hinders comparisons among different methods. Inspired loosely by the continuous inverse-variance weighting (IVW) method for minimizing variance of aggregated random variables [58], we develop a method for choosing a discrete, stable subset of relevant evaluations. We compute the variability of a progressively growing set of evaluations, starting from least variable and incrementally adding more variable ones, in ascending order. For a subset of size N, $std(E_1...E_N) = \sqrt{\frac{1}{N^2} \sum_i var(E_i)}$. Because of the $1/N^2$ scaling, adding more datasets decreases the variability of the average (Fig. 3 (right)) to a critical point. However, adding highly variable evaluations outweighs this term, increasing the average variability. We limit the evaluation set to remain highly reliable (i.e. with lower variability than the most reliable individual evaluation (<0.15)) while still including as many evaluations possible to maximize coverage and diversity, yielding the 27 *StableEval* set.

Training Configurations. We implement our model with the `big_vision` codebase [11], following the contrastive pretraining setup of SigLIP [190]. Unless otherwise specified, we train for 3 billion total samples seen, with a batch-size of $b{=}32,678$ with the sigmoid contrastive loss (Eq. (7)). The image-encoder takes images resized to $(256{\times}256)$ without any additional augmentations. The text-encoder uses a sentencepiece tokenizer [80] trained on English-C4 [120], with a vocabulary size of $32,000$. We truncate all text captions to the first 64 tokens. For most experiments, we use an rsqrt learning rate scheduler [189], with a peak learning-rate of 0.001, and linear-warmup and linear-cooldown applied for 10% of total steps. By default, we use a filtering ratio of $f{=}0.8$ when using *ACID* sampling, leading to a super-batch-size of $B{=}163,840$. We sweep over $\lambda{=}\{0.5, 1.0, 2.0\}$ for finding the optimal loss-weight for the *Softmax-KD* loss (Eq. (3)). For more details, refer to supplementary.

4.2. ACID is an effective distillation method

4.2.1. Scaling behaviour

To study the efficacy of *ACID* as an effective distillation method, we first conduct a scaling study as the reference/teacher model size is increased. We use Hard-*ACID* as our sampling scheme, and start with three fixed student models, Ti, S and B. We train each student by sweeping over (Ti, S, B, L, H and g) reference model sizes. Each reference model is trained on the WebLI-curated++ dataset for 2B samples seen, to ensure that the only difference across the experimental sweep is the size of the reference. Fig. 4 (left) showcases the scaling behaviour of each of the trained students, as the reference model is scaled up. We observe that across all student and reference models, our *ACID* method always outperforms the IID-baseline (dotted lines). Moreover, we note that the best reference-student combination (highlighted with ⋆) changes as we scale up the student sizes—the B reference is best for the Ti student, L reference for S student, and g reference for B student. This suggests an optimal *reference-student capacity ratio*—we can continue scaling up the reference model for *ACID* sampling until we hit this capacity ratio, beyond which performance saturates.

In Fig. 4 (right), we compare the scaling behaviour of our *ACID* variants (both I- and H-) with the *Softmax-KD* baseline, using an S student model. We note that across all reference/teacher scales, our *ACID* methods are more effective at distilling the knowledge into the smaller S student. Moreover, both versions of our method outperform the IID baseline, even when using a smaller Ti reference model. Contrarily, *Softmax-KD* only benefits when using much larger teacher models—this further demonstrates the scalability and flexibility of our *ACID* distillation. Since *H-ACID* demonstrates better scaling than *I-ACID*, we use that as our default in all further sections, and refer to it as our canonical *ACID* (dropping the H- for better readability).

4.2.2. ACID outperforms standard distillation

Having demonstrated the scaling behaviour of *ACID* and showcasing favourable performance comparisons to *Softmax-KD* using a single reference/teacher model dataset, we next demonstrate that *ACID* outperforms explicit distillation methods across different teacher/reference pretraining datasets, distillation objectives, and student model sizes.
Reference/Teacher Training Dataset. In Fig. 5 (left), we sweep over two different pretraining datasets for the references/teachers. We train an L-sized teacher/reference for 2B samples seen on WebLI-curated++ and WebLI. Using these models as teacher/reference, we train S students with *ACID*, that strongly outperform *Softmax-KD* for both datasets.
Different Distillation Objectives. Prior work has explored several different objectives for multimodal distillation, beyond standard *Softmax-KD*. Here, we compare our *ACID* method to some of these, including a *Sigmoid-KD* loss [173]
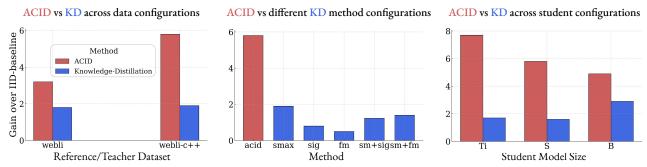
Figure 5. **ACID significantly outperforms KD.** *(left)* We vary the training dataset of the reference/teacher model, and use *the same pretrained model* as the reference for *ACID* and teacher for KD—across all configurations, we note strong gains for *ACID*. *(center)* Across different distillation objectives and a full hyperparameter sweep for optimal KD conditions, *ACID* is still the best performing method by large margins. *(right) ACID* further outperforms KD across three different student sizes.
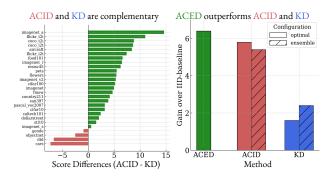

Figure 6. **ACED for improved distillation.** *(left)* Despite *ACID* outperforming KD across most benchmarks, it still suffers on 4 out of 27 evals (potentially due to filtering out data). This motivates that combining *ACID* and *KD* would enable a stronger, more robust model. *(right)* Our combined *ACED* indeed outperforms both *ACID* and *KD*, even when using an ensemble of teacher/reference models for *ACID* and *KD*, showcasing its generality.

and a *Feature-Matching KD* loss [180] (see supplementary for details). Further, the SoTA multimodal distillation method, CLIP-KD [180], advocates combining these losses for best performance. We therefore also compare against two combination methods—*Softmax+Sigmoid* and *Softmax+Feature-Matching*. In Fig. 5 (center), we show that *ACID*, without any additional complexity, still comprehensively outperforms all of the other distillation objectives.

Different Student Sizes. Finally, we also sweep across student sizes—Ti, S, and B. From Fig. 5 (right), we again observe that our *ACID* substantially improves over *Softmax-KD*. Interestingly, we note that our *ACID* method is more effective for smaller students (Ti, S) than the larger B student, whereas this is the opposite for the *Softmax-KD* baseline.

4.3. ACED: ACID and KD are complementary

Combining ACID and Softmax-Distillation—Why? Theoretically in Sec. 3.2, we show *ACID* is in fact a form of implicit distillation, yet the exact form of this objective is different from traditional distillation. As a result, here we ask if this form of distillation (although stronger than traditional

KD) is in fact complementary to standard distillation. This line of inquiry is further supported by an empirical finding shown in Fig. 6 *(left)*—while *ACID* outperforms *Softmax-KD* by more than 5% on tasks like COCO and Flickr retrieval, it underperforms *Softmax-KD* on more finegrained evaluations like Cars and DTD. This suggests that despite the implicit distillation performed by *ACID*, having an explicit distillation objective should further provide wider benefits.

ACED—How to combine? We now discuss strategies for combining *ACID* and *Softmax-KD*. The simple strategy, *ACIDistill*, samples a training batch using *ACID* and applies both the contrastive and softmax-distillation loss on that batch. An alternative strategy, *IIDistill*, samples two batches independently, one with *ACID* sampling and the other IID sampled, and applies the distillation loss on the IID batch while the contrastive loss is applied on the *ACID* batch. We study the scaling behaviour of both these strategies by training a ViT-S student with a WebLI-L teacher and a WebLI-curated++-reference model, for 3B, 6.5B and 13B samples seen. We observe that the *ACIDistill* method showcases better performance across all compute budget scales (see supplementary). Hence, going forward, we use *ACIDistill* as the default strategy for combining *ACID* and *Softmax-KD*, and refer to that as our main *ACED* method.

How well does ACED perform? We now compare our optimal *ACED* method from before with the *ACID* and *Softmax-KD* methods applied independently. First, we find that our *ACED* indeed outperforms both the independent methods, demonstrating that we are effectively able to leverage both the reference and teacher models. As an additional ablation, we also conduct a comparison with an ensemble version of *ACID* and *Softmax-KD*, where we use both the WebLI-L and WebLI-curated++-L models as a two-teacher ensemble for *Softmax-KD* and a two-reference ensemble for *ACID*. We find that *ACED* even outperforms these ensemble methods, suggesting that the benefits of our *ACED* are not solely due to using multiple teacher and reference models, but rather due to optimally combining the two frameworks.

Table 2. ***ACED* outperforms all prior state-of-the-art methods.** We showcase results for our method at three different model inference-GFlop scales. Across all three model scales, our *ACED* models' performance improves on the prior SoTA across the 27 StableEval evaluations, while using fewer inference FLOPs. For better interpretability, we also break down the evaluations into individual benchmarks (*e.g.*, ImageNet, COCO) and groupings (*e.g.*, ImageNet distribution shifts, other object categorization, and scene classification—for details, see supplementary). *MobileCLIP samples seen include two captions for each image, effectively doubling the total unique pairs.**TinyCLIP models are not trained from scratch, but use a complex weight inheritance strategy from pretrained models.

Method	Samples Seen	Infer. GFlops	Zero-shot Classification				Retrieval		Avg. Perf. (27 evals)
			IN-val	IN-shift	Object-Centric	Scene-Centric	COCO	Flickr30k	
DatologyAI-cls-S/32	2.0B	2.83	52.7	36.6	68.3	47.0	30.2	48.6	50.5
DatologyAI-ret-S/32	2.0B	2.83	45.6	35.9	61.9	44.9	41.5	64.0	49.3
TinyCLIP-RN30M	15.2B**	6.93	59.1	43.0	70.2	52.7	43.3	71.2	56.6
TinyCLIP-45M/32	15.8B**	3.70	62.7	48.3	74.8	56.6	45.4	72.1	60.4
TinyCLIP-63M/32	15.8B**	5.65	64.5	50.4	76.4	58.3	47.7	75.5	62.1
MobileCLIP-S0	13B*	3.70	67.8	55.2	77.0	57.3	49.6	76.7	63.6
ACED-F0	**13B**	**3.30**	**68.5**	**56.1**	**77.9**	**59.4**	**51.0**	**79.5**	**64.0**
DatologyAI-cls-B/32	5.1B	7.39	63.2	47.1	75.4	52.2	38.5	60.8	58.5
DatologyAI-ret-B/32	5.1B	7.39	55.8	45.9	69.6	53.5	49.6	72.6	57.3
CLIP-KD-RN50	0.5B	9.09	54.9	41.6	61.8	50.0	43.5	71.4	52.2
OpenAI-RN50	13B	9.09	59.8	44.6	65.2	50.9	38.7	68.6	53.6
OpenAI-CLIP-B/32	13B	7.39	63.3	50.3	72.6	55.2	40.3	68.9	58.6
LAION-CLIP-B/32	34B	7.39	66.6	52.4	78.4	59.5	47.7	75.5	63.7
DataComp-CLIP-B/32	13B	7.39	69.2	56.1	80.0	59.3	45.4	70.1	64.6
MetaCLIP-CLIP-B/32	13B	7.39	67.7	55.1	77.9	59.2	46.7	73.0	63.9
CLIP-CID-B/32	7.2B	7.39	62.7	50.5	(-)	(-)	(-)	(-)	(-)
TinyCLIP-39M/16	20B**	9.48	63.5	50.6	71.6	56.7	46.9	75.6	59.5
MobileCLIP-S1	13B*	7.64	72.6	63.3	80.4	61.6	53.0	80.0	67.9
ACED-F1	**13B**	**7.14**	**74.9**	**67.3**	**81.8**	**64.0**	**55.6**	**84.7**	**69.7**
OpenAI-RN101	13B	12.75	62.3	49.7	68.4	53.7	40.3	68.6	56.5
MobileCLIP-S2	13B*	10.81	74.4	68.1	81.8	63.6	54.4	81.8	69.8
ACED-F2	**13B**	**10.29**	**76.9**	**70.7**	**82.3**	**64.6**	**58.3**	**85.3**	**70.9**

Table 3. **LiT-Decoder Evaluations.**

Method	Samples Seen	Image GFlops	Captioning	VQA	
			Flickr30k	VQAv2	GQA
SigLIP-B/16	40B	23.45	53.4	64.5	54.9
SiLC-B/16	20B	23.45	49.2	65.7	54.1
ACED (B/16)	**13B**	**23.19**	**55.5**	**66.6**	**55.4**

4.4. Comparison to Prior Art

We now use our *ACED* method to pretrain models at large compute budgets, across three FLOP-scales, and compare with SoTA inference-efficient two-tower VLMs, including MobileCLIP [155], TinyCLIP [173], CLIP-KD [180], and CLIP-CID [183] (see supplementary for details). We further compare against the recently released DatologyAI CLIP models [3] (in grey), which have proprietary data curation strategies specific for classification and retrieval tasks independently. We train our *ACED*-F0, *ACED*-F1 and *ACED*-F2 models on the DataComp-1B dataset for 13B samples seen for a fair comparison. From Tab. 2, we observe that our *ACED* models are more FLOP-efficient and highly performant compared to other baselines in their respective classes—*ACED*-F0 outperforms MobileCLIP-S0 by 0.4% and TinyCLIP-63M/32 by 1.9%, on average, while being 10.81% and 41.5% more FLOP-efficient respectively; our *ACED*-F1 outperforms MobileCLIP-S1 by 1.8%, and

TinyCLIP-39M/16 by 10.2%, on average, while being 6.5% and 24.6% more efficient respectively; *ACED*-F2 outperforms MobileCLIP-S2 by 1.1% on average, while being 4.8% more FLOP-efficient. Notably, on the most widely-used evaluations like ImageNet, COCO and Flickr, our method surpasses the previous SoTA by large margins—*ACED*-F0 outperforms MobileCLIP-S0 by 0.7% on ImageNet, 1.5% on COCO, and 2.8% on Flickr; *ACED*-F1 outperforms MobileCLIP-S1 by 2.3% on ImageNet, 2.6% on COCO, and 4.7% on Flickr, while *ACED*-F2 outperforms MobileCLIP-S2 by 2.5% on ImageNet, 3.9% on COCO, and 3.5% on Flickr. In fact, our *ACED*-F1 model even outperforms MobileCLIP-S2 on ImageNet, while having 34% lesser GFlops (see Fig. 1). This further validates the scalability of our *ACED*, especially given our models *do not* use any bespoke architectures or complex augmentations.

4.5. ACED yields better encoders for other tasks

We next evaluate the benefits of *ACED* specifically for training an auto-regressive text-decoder with a frozen image-encoder, in the LiT-Decoder setting [13]. We evaluate the trained LiT-decoder models on Flickr30k [116] captioning (using the CIDEr metric [156]) and visual-question-answering (using accuracy) tasks. Since prior works on these evaluation benchmarks use bigger foundation models (*e.g.*,

SigLIP [190] and SiLC [108]), we also train a larger *ACED* (B/16) model for 13B samples seen for fair comparison. Tab. 3 demonstrates that our *ACED* model outperforms both strong baselines across both tasks—particularly, our model outperforms competitors that have similar image-GFlops but are trained for a *significantly higher number of samples seen* (up to ∼3x). This further highlights the impact of *ACED* particularly for distilling knowledge in the image-encoders.

5. Conclusion

In this work we showed that active data curation implicitly implements a novel form of distillation, which combines knowledge from both a reference model and the data itself. With this insight, we developed *ACID*, a powerful method for distilling large multimodal encoders into much more efficient ones via online joint-example selection [35]. *ACID* strictly outperforms traditional forms of knowledge distillation in training contrastive VLMs. Given that *ACID* implicitly optimizes a different objective than traditional softmax-based KD, we further demonstrated these two objectives to be complementary, arriving at our final method, *ACED*, which combines the benefits of each. Using *ACED* we distilled models that set a new state-of-the-art for FLOP-efficient zero-shot classification and image-text reasoning.

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A. Evaluation Protocol Details

In the main text in Sec. 4.1, we described the motivation and methodology for choosing our *StableEval* set of 27 evaluations. We also categorized our main results in Tab. 2 into IN-shift, Object-Centric, and Scene-Centric, under the zero-shot classification section. We now provide additional details for these sections.

***StableEval* Protocol.** For rigorously defining our final evaluation suite, we first selected 34 candidate evaluation datasets popularly used for evaluating standard image-text contrastive pretraining [48, 84, 119] and adaptation [49, 129, 152, 193, 198] methods. These datasets ranged from standard natural image-classification, to fine-grained classification of birds, animals, and cars etc., to different domains of images like satellite imagery and street signs. The full set of 34 candidate evaluations we started with are: FGVC-Aircrafts [104], Oxford Flowers-102 [112], Oxford-IIIT Pets [115], Stanford Cars [78], Food-101 [15], Caltech-101 [86], CIFAR-10 [79], CIFAR-100 [79], Pascal VOC 2007 [36], EuroSAT [60], RESISC45 [64], STL-10 [28], SUN-397 [174], Dollar Street [127], GeoDE [121], Country211 [119], FMoW [26], DTD [27], iWildCam [10], PatchCamelyon [157], CLEVR Counts [72], CLEVR Distance [72], KITTI Distance [51], ImageNet-V2 [125], ImageNet-A [62], ImageNet-R [61], ObjectNet [8], ImageNet-Val [30], ImageNet-Sketch [164], Rendered SST2 [119], Flickr30k (I2T and T2I) [116], MSCOCO ((I2T and T2I)) [96].

We then trained several variants of standard SigLIP and CLIP models with a ViT-S/32 image-encoder and a BERT-small text-encoder, to quantify the amount of variance present for each evaluation dataset, solely due to the random seed (*i.e.*, different initialization of model weights). Specifically, we first trained 5 IID-SigLIP models on both DataComp-1B and WebLI-1B for 3B examples seen (*i.e.*, with randomly sampling batches of data at each step) by only changing the random seed. Note that we ensured that the exact samples seen per step in the training process was fixed—that is, the only randomness across the 5 different seed runs was the model initialization. We also trained an IID-CLIP model for 5 seeds to add variation on the training objective to the set of models. We then get the average standard deviation of each evaluation dataset by first averaging over the 5 different random seeds per method (*i.e.*, DataComp-IID-SigLIP, DataComp-IID-CLIP, WebLI-IID-SigLIP), and then averaging over the 3 different combinations of methods. This average standard deviation is taken to be the variability of each evaluation, which is shown in Fig. 3. We also tested this variability across other settings by changing the patch-size of the image-encoder (from S/32 to S/16) and increasing the model size (from S/32 to B/32), and found the variability (standard deviation) per evaluation dataset to be consistent.

Equipped with these standard deviations per evaluation dataset, we then aim to prune out the set of highly unstable evaluations from the full set of 34 evaluations by taking inspiration from the continuous inverse-variance weighting (IVW) method [58]. We start with the lowest-variance evaluation (Country211 with 0.15% standard deviation), and progressively add evaluations in increasing order of their computed standard deviations, each time computing the variability of the average over the current set of evaluations. For a set of N evaluations, the variability of the average is computed as $std(E_1...E_N) = \sqrt{\frac{1}{N^2}\sum_i var(E_i)}$. At each step, we compare the variability of the average with the variability of the most reliable evaluation (*i.e.*, Country211 with 0.15% standard deviation), and prune out all evaluations beyond the critical point where the variability of the average becomes larger than the Country211 variability. This leaves us with a set of 27 evaluations that are both diverse as well as stable across different random seeds. The 7 evaluation datasets that were pruned out of the final set are: EuroSAT, CLEVR Counts, GTSRB, iWildCam, SVHN, KITTI Distance, CLEVR Distance, PatchCamelyon, and Rendered-SST2.

Categorization of Datasets. Having identified our stable set of evaluation datasets, we next categorize them into different brackets for easier parsing of the different capabilities of the models in Tab. 2. In Tab. 4, we showcase the breakdown of the different categories represented in Tab. 2 for all 27 evaluations. We categorize them into *object-centric* datasets like FGVC-Aircrafts or Stanford Cars, *scene-centric* datasets like SUN-397 or RESISC45, *Imagenet-based natural distribution shifts* like ImageNet-V2 or ObjectNet, and other *miscellaneous* evaluations like DTD or Country211. Finally, we also evaluate our models on image-text retrieval datasets like COCO and Flickr, both using text-to-image retrieval and image-to-text retrieval, as separate evaluation metrics.

Table 4. **Final *StableEval* Set of** 27 **evaluations.**

Category	Dataset	Task	Test set size	Number of classes
Object-Centric	FGVC-Aircrafts [104]	Aircraft recognition	3,333	100
	Oxford Flowers-102 [112]	Flower recognition	6,149	102
	Oxford-IIIT Pets [115]	Pet classification	3,669	37
	Stanford Cars [78]	Vehicle recognition	8,041	196
	Food-101 [15]	Food recognition	25,250	101
	Caltech-101 [86]	Object recognition	6,085	102
	CIFAR-10 [79]	Visual recognition	10,000	10
	CIFAR-100 [79]	Visual recognition	10,000	100
	Pascal VOC 2007 [36]	Object recognition	14,976	20
	STL-10 [28]	Visual recognition	8,000	10
Scene-Centric	SUN-397 [174]	Scene recognition	108,754	397
	GeoDE [121]	Object/scene recognition	12,488	40
	RESISC45 [64]	Satellite imagery recognition	6,300	45
	FMoW [26]	Satellite imagery recognition	22,108	62
Distribution-shifts	ImageNet-V2 [125]	Visual recognition	10,000	1,000
	ImageNet-A [62]	Visual recognition	7,500	200
	ImageNet-R [61]	Visual recognition	30,000	200
	ObjectNet [8]	Visual recognition	18,574	113
Misc.	ImageNet-Val [30]	Visual recognition	50,000	1,000
	ImageNet-Sketch [164]	Visual recognition	50,889	1,000
	DTD [27]	Texture classification	1,880	47
	DollarStreet [127]	Object recognition	3,503	58
	Country211 [119]	Geolocation	21,100	211
Retrieval	Flickr30k (I2T, T2I) [116]	Image and text retrieval	31,014	N/A
	MSCOCO (I2T, T2I) [96]	Image and text retrieval	5,000	N/A

B. Image-text contrastive Objectives

Here, we expand the full image-text pretraining objectives described in Sec. 3.1. The per-sample softmax image-text objective is primarily used for training CLIP [119] models, while the per-sample sigmoid objective is primarily used in training SigLIP [190] models:

$$\mathcal{L}_{\text{softmax}}(x_i; \mathcal{B}) = -\frac{1}{2}\left(\log p_{ii}^{\text{img}\rightarrow\text{txt}} + \log p_{ii}^{\text{txt}\rightarrow\text{img}}\right) \tag{6}$$

$$\mathcal{L}_{\text{sigmoid}}(x_i; \mathcal{B}) = -\left(\log p_{ii}^{\text{sig}} + \sum_{j=1, j\neq i}^{b} \log(1 - p_{ij}^{\text{sig}})\right) \tag{7}$$

C. Proofs for Active Curation as Implicit Distillation

In this section, we provide derivations for our theoretical results in Sec. 3.2 showcasing the equivalence between active data curation and knowledge distillation. We first show the proof for the case where we use easy-reference scoring for data-curation, followed by the learnability-scoring case, and finally showcase a generalized version of the proof.

Setup. Recollect from the main paper text in Sec. 3.2, that we are given an image-text pretraining dataset $\mathcal{D}$. The simple training approach is to sample uniformly random batches of data $\mathcal{B}$ (of size b), from $\mathcal{D}$ at each step t, and minimize $\mathcal{L} \in \{\mathcal{L}_{\text{softmax}}, \mathcal{L}_{\text{sigmoid}}\}$ (see Appendix B for full equations for the loss objectives). We call this baseline, minimizing $\hat{\mathcal{L}} = \frac{1}{b} \sum_{x_i \sim \mathcal{U}[\mathcal{D}]} \mathcal{L}(x_i; \mathcal{B})$ as the *IID-baseline* (θ_{IID}). Further, remember that in the *active data curation* setup, we employ a smarter way to select batches, using a pretrained *reference* model θ_{ref}. At each step t, we select a sub-batch $\mathcal{B}$ (size b) from a much larger super-batch $\mathcal{S}$ (size B) according to an *active selection distribution* $\mathcal{A}[\mathcal{S}]$.

<u>A</u>ctive Data <u>C</u>uration as <u>I</u>mplicit <u>D</u>istillation (ACID). We now show formally that active curation can be cast as "implicit distillation" and should benefit from larger reference models. The model now minimizes $\hat{\mathcal{L}} = \frac{1}{b} \sum_{x_i \sim \mathcal{A}[\mathcal{S}]} \mathcal{L}(x_i; \mathcal{B})$, which in expectation is $\mathcal{E} = \mathbb{E}[\hat{\mathcal{L}}] = \sum_{x \in \mathcal{D}} a(x)\mathcal{L}(x; \mathcal{B})$ given that super-batches $\mathcal{S}$ are sampled uniformly. Recall that $\mathcal{L}(x; \mathcal{B}) = -\sum_{i=1}^{b} y_i(x) \log q_i(x)$, where y_i are the labels of the contrastive task and q_i are the probabilities induced by the pairwise similarities of the student θ. Let p_i be the probabilities induced by the reference model θ_{ref}. In the case of *easy-reference scoring* and the softmax loss, $a(x) = \frac{1}{Z} \exp \sum_{i=1}^{b} y_i(x) \log p_i(x) = \frac{1}{Z} p_{i^*}(x)$ where i^* is the index of the one-hot label $y(x)$. As such,

$$\mathcal{E}_{\text{easy-ref}} = -\sum_{x \in \mathcal{D}} a(x) \sum_{i=1}^{b} y_i(x) \log q_i(x) \tag{8}$$

$$= -\frac{1}{Z} \sum_{x \in \mathcal{D}} p_{i^*}(x) \sum_{i=1}^{b} y_i(x) \log q_i(x)$$

$$= -\frac{1}{Z} \sum_{x \in \mathcal{D}} \sum_{i=1}^{b} p_{i^*}(x) y_i(x) \log q_i(x)$$

$$= \frac{1}{Z} \sum_{x \in \mathcal{D}} \text{KD}[p(x) \cdot y(x); q(x)]$$

This demonstrates that by curating data according to the reference model θ_{ref}, we implicitly distill its knowledge via a novel data-driven objective, using a combination of model predictions and real labels as targets. We next prove the equivalence of data curation and knowledge-distillation, when using learnability-based scoring for our active data curation.

Learnability-based Data Curation is Hard Distillation. When using learnability-based prioritization, the active selection distribution $\mathcal{A}$ factorizes as $a^{\text{learn}} = \frac{1}{Z} \exp(s^{\text{learn}}) = \frac{1}{Z} \exp[\mathcal{L}(\cdot|\theta) - \mathcal{L}(\cdot|\theta_{\text{ref}})] = a^{\text{easy-ref}} \cdot a^{\text{hard-learn}}$ where $a^{\text{hard-learn}} = \frac{1}{Z} \exp[\mathcal{L}(\cdot|\theta)]$ prioritizes examples with high loss according to the student. Since easy-reference prioritization yields implicit distillation (*I-ACID*, Eq. (4)), learnability prioritization yields:

$$\mathcal{E}_{\text{learn}} = \sum_{x \in \mathcal{D}} a^{\text{hard-learn}}(x) \cdot a^{\text{easy-ref}}(x)\mathcal{L}(x; \mathcal{B}) \tag{9}$$

$$= \frac{1}{Z} \sum_{x \in \mathcal{D}} a^{\text{hard-learn}}(x)\text{KD}[p(x) \cdot y(x); q(x)]$$

This demonstrates that learnability-based active curation is equivalent to implicit distillation on hard examples ("H-ACID") according to the student model.

ACID for general learning objectives. In the general case (including sigmoid-contrastive learning, and combined image-to-text and text-to-image softmax contrastive learning), $y(x)$ contains a set of labels $y_i(x)$ such that $\sum_{i=1}^{b} y_i(x) = 1$. In this case

$a(x) = \frac{1}{Z} \exp \sum_{i=1}^{b} y_i(x) \log p_i(x) \leq \frac{1}{Z} \sum_{i=1}^{b} y_i(x) p_i(x) = \frac{1}{Z} \hat{p}(x)$ due to the convexity of the exponential. In particular,

$$\mathcal{E}_{\text{easy-ref}} = - \sum_{x \in \mathcal{D}} a(x) \sum_{i=1}^{b} y_i(x) \log q_i(x) \geq - \frac{1}{Z} \sum_{x \in \mathcal{D}} \hat{p}(x) \sum_{i=1}^{b} y_i(x) \log q_i(x) \tag{10}$$

$$\geq \frac{1}{Z} \sum_{x \in \mathcal{D}} \text{KD}[\hat{p}(x) \cdot y(x); q(x)] \tag{11}$$

As such, learning from actively-curated data minimizes an upper bound on the KD objective described previously, for general learning objectives of the form $\sum_{i=1}^{b} y_i(x) \log q_i(x)$, including the softmax- and sigmoid-contastive objectives we utilize in this work.

D. Knowledge Distillation Objectives

In this section, we describe in detail all the knowledge-distillation methods we use to compare as baselines in our results in Sec. 4.2. Given the student model θ and a pretrained teacher model θ_{teacher}, we considered three main objectives for distilling the knowledge from the teacher θ_{teacher} into the student model θ.

Softmax contrastive distillation. Here, our aim is to distill the contrastive logit matrix from the teacher to the student. Formally, given a data-batch B, we extract teacher embeddings $\{(z_{i,t}^{\text{img}}, z_{i,t}^{\text{txt}})\}$ and student embeddings $\{(z_{i,s}^{\text{img}}, z_{i,s}^{\text{txt}})\}$. The teacher and student contrastive matrices, $\mathcal{T}_{b\times b}$ and $\mathcal{S}_{b\times b}$, contain the teacher and student image-text logits, respectively:

$$\mathcal{T}_{i,j} = \alpha_t z_{i,t}^{\text{img}} \cdot z_{j,t}^{\text{txt}}, \mathcal{S}_{i,j} = \alpha_s z_{i,s}^{\text{img}} \cdot z_{j,s}^{\text{txt}} \tag{12}$$

Our softmax distillation objective takes the form of a cross-entropy loss between the teacher and student contrastive matrices, considering the texts as labels by applying a row-wise softmax on the contrastive matrices ($\mathcal{T}$, $\mathcal{S}$) and the images as labels by applying a column-wise softmax ($\mathcal{T}^T$, $\mathcal{S}^T$).

$$\mathcal{L}_{\text{smax-dist}} = -\frac{1}{2b} \sum_{i=1}^{b} \left(\underbrace{\texttt{softmax}(\mathcal{T}_{i,\cdot}) \log \texttt{softmax}(\mathcal{S}_{i,\cdot})}_{\text{image-to-text}} + \underbrace{\texttt{softmax}(\mathcal{T}_{i,\cdot}^T) \log \texttt{softmax}(\mathcal{S}_{i,\cdot}^T)}_{\text{text-to-image}} \right) \tag{13}$$

Sigmoid contrastive distillation. Similarly as above, here we distill the teacher contrastive matrix into the student matrix. However, differently from the softmax case, in this loss we use the full teacher and student image-text logits with the addition of the bias term:

$$\mathcal{T}_{i,j} = \alpha_t z_{i,t}^{\text{img}} \cdot z_{j,t}^{\text{txt}} + \beta_t, \mathcal{S}_{i,j} = \alpha_s z_{i,s}^{\text{img}} \cdot z_{j,s}^{\text{txt}} + \beta_s \tag{14}$$

Our sigmoid distillation objective then simply takes the form a binary cross-entropy objective between the teacher and the student logits (converted to probabilites using the sigmoid (σ) activation):

$$\mathcal{L}_{\text{sig-dist}} = -\frac{1}{b} \sum_{i=1}^{b} \left(\sigma(\mathcal{T}_{i,\cdot}) \log \sigma(\mathcal{S}_{i,\cdot}) + \sigma(-\mathcal{T}_{i,\cdot}) \log \sigma(-\mathcal{S}_{i,\cdot}) \right) \tag{15}$$

Feature-matching distillation. We also explore a distillation loss that directly aligns the image and text embeddings of the student and teacher models directly, using a simple mean-squared error. Such a strategy has also been explored in prior SoTA CLIP distillation works [180], with great efficacy. If the student and teacher embedding dimensions are different, we project the student embedding to the teacher dimension using a learnable linear projection head P_{head}:

$$\hat{z}_{i,s}^{\text{img}} = z_{i,s}^{\text{img}} P_{\text{head}}, \hat{z}_{i,s}^{\text{txt}} = z_{i,s}^{\text{txt}} P_{\text{head}}$$

$$\mathcal{L}_{\text{fm-dist}} = \frac{1}{2b} \sum_{i=1}^{b} \left(\underbrace{\|\hat{z}_{i,s}^{\text{img}} - z_{i,t}^{\text{img}}\|_2^2}_{\text{image align}} + \underbrace{\|\hat{z}_{i,s}^{\text{txt}} - z_{i,t}^{\text{txt}}\|_2^2}_{\text{text align}} \right) \tag{16}$$

Students with Knowledge Distillation. For training student models with KD-objectives as specified above, we always use them in conjunction with the standard contrastive loss (either Eq. (6) or Eq. (7)):

$$\mathcal{L}_{\text{dist-only}} = \mathcal{L}_{\text{softmax/sigmoid}} + \lambda_{\text{smax}} \cdot \mathcal{L}_{\text{smax-dist}} + \lambda_{\text{sig}} \cdot \mathcal{L}_{\text{sig-dist}} + \lambda_{\text{fm}} \cdot \mathcal{L}_{\text{fm-dist}} \tag{17}$$

This objective allows us to flexibly combine the different distillation objectives by varying the different loss-weights $\lambda_{\text{smax/sig/fm}}$. By default, we use only the softmax distillation objective with a loss-weight of 2.0, however we perform sweeps over multiple configurations of loss-weights and loss-combinations in our experiments.

Ensemble Teachers. The above distillation setup also easily enables using multiple teacher models in an ensemble for teaching the student. Such an ensemble teacher strategy has been explored in prior SoTA multimodal distillation works [155]. For a

teacher ensemble, the distillation objective simply averages the predicted logits from the different teachers. As an example, an ensemble-softmax-distillation objective would be as follows:

$$\mathcal{L}_{\text{ens-smax-dist}} \quad = \quad -\frac{1}{2bK}\sum_{k=1}^{K}\sum_{i=1}^{b}(\underbrace{\texttt{softmax}(\mathcal{T}_{i,\cdot}^{k})\log\texttt{softmax}(\mathcal{S}_{i,\cdot})}_{\text{image-to-text}} + \underbrace{\texttt{softmax}(\mathcal{T}_{i,\cdot}^{k\,T})\log\texttt{softmax}(\mathcal{S}_{i,\cdot}^{T})}_{\text{text-to-image}}) \quad (18)$$

E. Training Details

Our default configuration follows that of SigLIP [190]. Unless otherwise specified, we train for 3 billion total samples seen, with a batch-size of $b=32,678$ with the sigmoid contrastive loss (Eq. (7)). The image-encoder takes images resized to (256×256) without any additional augmentations. By default for all our ablation experiments, we use a ViT-S/16 image encoder and a BERT-small text encoder. The image encoder uses global-average pooling (GAP) for the final embedding by default, however for some experiments we also use multi-head attention pooling (MAP) [85, 189]. The text-encoder uses a sentencepiece tokenizer [80] trained on the English-C4 [120] dataset, with a vocabulary size of $32,000$. We truncate all text captions to the first 64 tokens. For most experiments, we use an rsqrt learning rate scheduler [189], with a peak learning-rate of 0.001, and linear-warmup and linear-cooldown applied for 10% of total steps. However, for some of our final method comparisons in Tab. 2, we use a cosine learning rate scheduler [131] with a linear-warmup applied for 10% of total steps and peak learning-rate of 0.001. By default, we use a filtering ratio of $f=0.8$ when using *ACID* sampling, leading to a super-batch-size of $B=163,840$. We additionally use an ACID sampling temperature of $\tau=10$ for all our experiments. We sweep over $\lambda=\{0.5,1.0,2.0\}$ for finding the optimal loss-weight for the *Softmax-Distillation* loss (Eq. (3)). We use a weight decay of 0.0001, gradient clipping to a maximum norm of 1.0, and the Adam optimizer with ($\beta_1=0.9$, $\beta_2=0.95$). All our experiments are conducted with `big_vision` [11] using `jax` [16].

F. About baselines and final ACED models

In this section, we describe the exact architectural details of all the baselines and our ACED models in Tab. 5.

Table 5. **Architectural Details of baselines and *ACED*-F* models.** For each of the baselines and our own *ACED* models, we provide the exact image and text encoder architectures used, the image-resolution used for training, the patch-size for vision-transformer specific encoders, the text sequence-length, training dataset and total compute budget for training in terms of total samples seen.

Method	Samples Seen	Infer. GFlops	Pretraining Dataset	Image Encoder	Text Encoder	Image Resolution	Image Patch Size	Text Seq. Len.
DatologyAI-cls-S/32	2.0B	2.83	Datology-Proprietary	ViT-S/32	BERT-small	224	32	77
DatologyAI-ret-S/32	2.0B	2.83	Datology-Proprietary	ViT-S/32	BERT-small	224	32	77
TinyCLIP-RN30M	15.2B**	6.93	LAION-400M	RN-30M	Custom	224	(-)	77
TinyCLIP-45M/32	15.8B**	3.70	LAION+YFCC-400M	ViT-65M/32	Custom	224	32	77
TinyCLIP-63M/32	15.8B**	5.65	LAION+YFCC-400M	ViT-63M/32	Custom	224	32	77
MobileCLIP-S0	13B*	3.70	DataCompDR-1B	MCi0	MCt	256	(-)	77
ACED-F0	13B	3.30	DataComp-1B	ViT-S/32	BERT-small	256	32	64
DatologyAI-cls-B/32	5.1B	7.39	Datology-Proprietary	ViT-B/32	BERT-base	224	32	77
DatologyAI-ret-B/32	5.1B	7.39	Datology-Proprietary	ViT-B/32	BERT-base	224	32	77
CLIP-KD-RN50	0.5B	9.09	CC-3M+CC-12M	RN-50	BERT-base	224	(-)	77
OpenAI-RN50	13B	9.09	OpenAI-WIT	RN-50	BERT-base	224	(-)	77
OpenAI-CLIP-B/32	13B	7.39	OpenAI-WIT	ViT-B/32	BERT-base	224	32	77
LAION-CLIP-B/32	34B	7.39	LAION-2B	ViT-B/32	BERT-base	224	32	77
DataComp-CLIP-B/32	13B	7.39	DataComp-1B	ViT-B/32	BERT-base	224	32	77
MetaCLIP-CLIP-B/32	13B	7.39	MetaCLIP-2B	ViT-B/32	BERT-base	224	32	77
CLIP-CID-B/32	7.2B	7.39	LAION-225M	ViT-B/32	BERT-base	224	32	77
TinyCLIP-39M/16	20B**	9.48	YFCC-15M	ViT-39M/16	Custom	224	16	77
MobileCLIP-S1	13B*	7.64	DataCompDR-1B	MCi1	BERT-base	256	(-)	77
ACED-F1	13B	7.14	DataComp-1B	ViT-B/32	BERT-small	256	32	64
OpenAI-RN101	13B	12.75	OpenAI-WIT	RN-101	BERT-base	224	(-)	77
MobileCLIP-S2	13B*	10.81	DataCompDR-1B	MCi2	BERT-base	256	(-)	77
ACED-F2	13B	10.29	DataComp-1B	ViT-B/24	BERT-small	240	24	64

G. Additional Experiments, Ablations and Results

In this section, we provide some additional ablations and more detailed results, augmenting those present in the main paper. We further also include additional baseline comparisons with proprietary models.
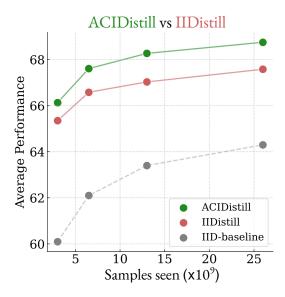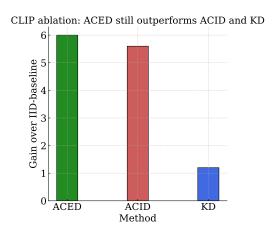
G.1. ACIDistill vs. IIDistill scaling

Figure 7. **How to combine ACID and KD in ACED?** The optimal scalable strategy for combining *ACID* and *Softmax-Distillation* is the *ACIDistill* method—where we apply both the contrastive and distillation losses on the *ACID* batch—this is both more performant and training-time efficient than the *IIDistill* scheme.

G.2. Softmax vs Sigmoid Pretraining

We have used SigLIP (sigmoid) pretraining for all our main results because of it's strong performance as a baseline. Here we show that the results are similar with CLIP (softmax) pretraining as well. Overall, the sigmoid variant is more scalable.
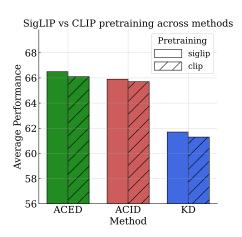

Figure 8. **CLIP vs SigLIP pretraining.** *(left)* Our *ACED* method when applied with CLIP pretraining instead of SigLIP, also further improves over both our *ACID* and *Softmax-KD* approaches. This showcases our methods' generality across pretraining objectives. *(right)* We compare all our methods across SigLIP and CLIP pretraining, and we observe that SigLIP pretraining clearly outperforms the CLIP objective across all the methods, justifying our choice of using it for all our final results.

G.3. ACID vs KD as we scale compute

In Sec. 4.2.2, we demonstrated that our *ACID* outperforms distillation methods across a variety of data-, student-size-, and method-configurations. However, all these results were at the 3B samples seen scale. Here, we compare *ACID* and *Softmax-Distillation* as we increase the training compute budget to 6.5B and 13B samples seen scale. Fig. 9 depicts that as we scale up the compute budget, *ACID* still strongly outperforms *Softmax-Distillation*, further signifying the scalability of our method.
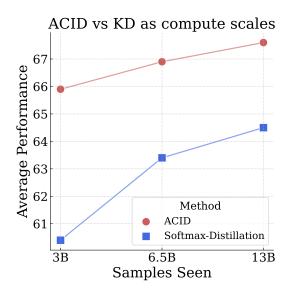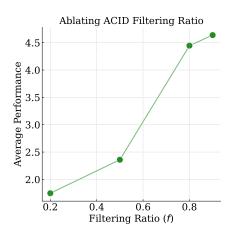

Figure 9. **ACID outperforms Softmax-Distillation across training compute budgets.**

G.4. Full Detailed Results across all 27 *StableEval* Evaluations

Table 6. **Full Detailed Per-Dataset Results of ACED models on the 27 *StableEval* Evaluations.**

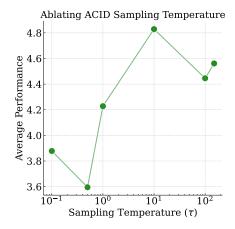|	FGVC-Aircrafts	Oxford-Flowers-102	Oxford-IIIT-Pets	Stanford Cars	Food-101	Caltech-101	CIFAR-10	CIFAR-100	Pascal VOC 2007	STL-10	SUN-397	GeoDE	RESISC45	FMoW	ImageNet-V2	ImageNet-A	ImageNet-R	ObjectNet	ImageNet-Val	ImageNet-Sketch	DTD	DollarStreet	Country211	Flickr30k I2T	Flickr30k T2I	COCO I2T	COCO T2I	Average (27)
ACED-F0	18.75	73.41	89.13	79.23	85.41	84.40	93.88	74.38	83.60	97.25	69.12	86.94	64.94	16.46	61.21	33.05	79.15	51.05	68.45	53.37	45.69	43.73	15.09	87.60	71.40	60.80	41.23	64.0
ACED-F1	26.94	79.59	91.31	83.32	89.96	85.24	96.69	81.68	84.39	98.78	73.13	90.49	69.49	23.09	67.80	53.35	87.93	60.24	74.92	61.55	51.54	48.49	20.28	90.30	77.92	64.96	47.27	69.7
ACED-F2	27.00	79.41	92.29	86.48	91.12	83.99	96.03	82.86	85.37	98.85	74.06	91.19	68.84	24.21	70.03	58.64	90.14	63.87	76.90	63.67	50.21	48.42	22.10	91.10	79.46	66.92	49.69	70.9

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G.5. Hyperparameter Sensitivity in ACID

Figure 10. **ACID hyperparameters.** *(left)* We observe that as we keep increasing the filtering ratio, we continue to see improved performance from $f=0.2$ to $f=0.8$. However, note that these improvements saturate at very high filtering ratios ($f=0.9$) due to very aggressive filtering which might lead to insufficient coverage of the entire data distribution. *(right)* We find a sampling temperature $\tau=10$ to be optimal across the range of sampling temperatures we tested, trading-off between deterministic top-k sampling (at very high temperatures) vs random sampling (at very low temperatures).

H. Extended Related Works

Multimodal Data Curation. Recent works have emphasised the importance of data quality for pretraining multimodal models [41, 48, 89, 106, 109, 153]. Canonical methods for curating high-quality training data generally involve static offline curation include removing noisy samples [1, 2, 19, 20, 48, 69, 103, 144, 160, 178], rebalancing concept distributions [2, 114, 178], improving quality of text captions [38, 82, 87, 88, 91, 110, 111, 182, 187, 192], and using pretrained data-selector models for filtering samples with low image-text alignment [42, 75, 101, 138, 139, 167–169, 186].

However, such static offline curation methods that pre-filter data do not take into account the training dynamics of the current learner model, and hence can suffer at larger scales [53]. Some prior works tackle this by introducing data selection criteria that account for the current state of the learner— Loshchilov and Hutter [100] proposed *online batch selection*, that at each step selects training samples that have the largest learner loss. Further works extended upon this idea by exploring different sample selection criteria, all based on the current learner state [40, 46, 67, 70, 73, 74, 81, 102, 132, 137, 143, 150, 170, 177, 197]. Further, Mindermann et al. [107] introduced the RHO-Loss that considers both current learner state and a pretrained data-selector (reference) model. Further works extended this criterion (termed *learnability scoring*) and scaled it to foundation model training [17, 31, 34, 35, 39, 66]. A key underlying goal of almost all of these prior data curation methods is to improve training efficiency by reducing the number of samples required for pretraining. Owing to this push for training efficiency, most pretrained reference models that are used as *data selectors are typically smaller than the learner models they are used to train* [34, 35, 42]. In fact, Fang et al. [42], Gadre et al. [48], Yu et al. [186] all showed that increasing the reference model size might even be detrimental for training a good learner model.

In this work, we show for the first time that *larger reference models can indeed be used as strong data selectors*, and showcase the conditions under which this simple active data-curation method can be used as an effective distillation strategy for training smaller learner models. Our experiments demonstrate that this can in-fact even outperform standard knowledge distillation strategies that are the most popular methods for compressing big models into smaller, more efficient ones.

Knowledge Distillation. First introduced by Buciluă et al. [18] and further popularized by Ba and Caruana [7], Hinton [65], knowledge distillation (KD) is a classic technique for transferring knowledge from a larger model (*teacher*) to another smaller one (*student*), by optimizing the student to match certain outputs (logits, features, intermediate activations etc.) of the teacher model. It has been extensively used for compressing large models into smaller, deployable ones in unimodal tasks like image-classification [12, 22, 25, 43, 47, 63, 113, 128, 149, 158, 165] and language representation learning [5, 55, 76, 95, 134, 146, 179]. Further works have extended KD to use multiple teacher-ensembles [21, 37, 105, 135, 141, 145, 185, 200], different distillation training objectives [68, 92, 122, 147, 151, 175, 196], and progressive multi-stage training schemes [6, 56, 93, 194, 195]. See Gou et al. [52] for a comprehensive survey of KD methods across a range of practical unimodal settings.

However, KD methods in the multimodal foundation model regime are underexplored. Some initial works [29, 44, 99, 166, 171] proposed strategies for efficiently compressing a multimodal teacher for captioning, visual question-answering and video retrieval tasks. Sameni et al. [133] introduced SF-CLIP, a method for improving CLIP pretraining via masked distillation, while Vasu et al. [155] proposed MobileCLIP, exploring downscaling CLIP models for mobile-deployment by using a combination of multi-teacher contrastive-KD, synthetic captions, and data-augmentations. Wu et al. [173] further proposed TinyCLIP—a weight inheritance method combined with an affinity-mimicking strategy for multimodal KD to yield tiny CLIP models. Yang et al. [180] conducted an extensive empirical study (CLIP-KD) into the different objective functions for effectively performing distillation of CLIP models, across different scales. Finally, CLIP-CID [183] uses an image semantic balancing strategy coupled with cluster-instance discrimination for better teacher-to-student knowledge transfer during the KD process. We compare against these methods as baselines for our experimental results in Sec. 4.

Accelerating Knowledge Distillation with Data Selection. There have been prior works attempting to make KD-based pretraining more efficient [140, 142, 188]. Some works [9, 83, 163, 176] have investigated accelerating vanilla KD using active learning in small-scale classification tasks. However, such approaches require a costly iterative process, involving synthetic generation, followed by active sample selection to produce pseudo-labels from a teacher model, thereby limiting their scalability. Another line of work studies data-selection methods for improving KD, typically using uncertainty-based data, logit and feature selection [59, 90, 97, 123, 130, 161, 162, 172, 199], contextual retrieval and sample augmentation from a large data pool [50, 71, 94, 98, 118, 124, 191], or influence-function based sample selection [83, 184]. Contrary to these works, Beyer et al. [12] and Hao et al. [57] suggest that vanilla knowledge distillation provides optimal gains in the "infinite-data regimes". All these prior works however operate primarily in the unimodal image or text classification regime, and none has been scaled up to multimodal foundation model training. We showcase, for the first time, that simple data selection using online batch selection outperforms standard KD for pretraining multimodal models. We further study the optimal strategies for combining vanilla KD and active data curation to best leverage their complementary strengths.

I. Discussion

Model-based active learning and knowledge-distillation are separate techniques that have traditionally targeted two very different problems. While active learning via online batch selection has focused on improving performance and efficiency of large-scale foundation model pretraining, knowledge-distillation methods seek to achieve highly inference-efficient models by transfer of knowledge from these larger foundation models. In this work, we show theoretically that in fact, active data selection can be cast as a form of implicit knowledge-distillation where the target distribution is now a product of reference (teacher) model probabilities and real labels. With this insight, we develop *ACID*, a powerful method for distilling efficient contrastive multi-modal encoders from larger reference models via online joint-example selection [35]. Notably, this method is a significant and initially counterintuitive departure from traditional active curation paradigms [34, 107] which typically seek reference models that are significantly cheaper in compute compared to the student.

We empirically validate that indeed *ACID* is a strong form of distillation that strictly outperforms traditional forms of knowledge-distillation in training contrastive VLMs. Given the different form of implicit distillation objective in *ACID*, we further demonstrate that this is complementary with traditional softmax-based KD, arriving at a final method, *ACED*, which combines the benefits of each. Using *ACID* we effectively distill models that achieve stronger zero-shot classification and image-text retrieval with cheaper inference FLOPs than prior SoTA methods.

I.1. Limitations

While we see our work as a novel, simple, and scalable paradigm for effective distillation of efficient models, our results are limited in scope to contrastive training of VLMs. Knowledge-distillation can in theory be applied to many problems such as supervised image classification [77], self-supervised learning [23, 54], etc. and it remains to be seen whether our results can be transferred to these domains. Furthermore, while we have shown that we can distill SoTA models that are efficient on a theoretical FLOPs basis, it remains to be seen whether our method can achieve SoTA results when constrained by device latency as is necessary for many edge deployments. We leave it to future work to benchmark our method with SoTA low-latency architectures like FastVIT [154] or MobileNet-V4 [117].