Efficient Vision-Language Pretraining with Visual Concepts and Hierarchical Alignment

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Abstract

Vision and Language Pretraining has become the prevalent approach for tackling multimodal downstream tasks. The current trend is to move towards ever larger models and pretraining datasets. This computational headlong rush does not seem reasonable in the long term to move toward sustainable solutions, and *de facto* excludes academic laboratories with limited resources. In this work, we propose a new framework, dubbed ViCHA, that efficiently exploits the input data to boost the learning by: (a) a new hierarchical cross-modal alignment loss, (b) new self-supervised scheme based on masked image modeling, (c) leveraging image-level annotations, called *Visual Concepts*, obtained with existing foundation models such as CLIP to boost the performance of the image encoder. Although pretrained on four times less data, our ViCHA strategy outperforms other approaches on several downstream tasks such as Image-Text Retrieval, VQA, Visual Reasoning, Visual Entailment and Visual Grounding. The code is available here: https://github.com/mshukor/ViCHA.

1 Introduction

Vision and Language Pretraining (VLP) [11, 21] consists of training a vision and language model with simple pretraining tasks, like image-text alignment or masked language modelling, usually on large datasets. It is becoming the prominent paradigm to solve multimodal vision-language tasks (*e.g.* VQA [4], NLVR^2 [68]), outperforming other task-customised approaches [2, 31]. The representation learned by these models have shown to be useful also for unimodal tasks, paving the way for more general or foundational models [55, 65, 86, 87].

Due to the abundance of image-text pairs data on the internet [10, 17, 60], scaling these models has gained a lot of attention. The current most efficient approaches are those beyond 1B parameters [1, 86] and trained on hundred of millions to several billions examples [30, 55, 77]. This race for bigger models/data, is most often done to the detriment of the quality of learning strategies, which becomes more and more difficult to control. We argue that a lot of improvements can be done by designing more efficient learning schemes. For example, while Dosovitskiy et al. [19] train Vision Transformers with a huge pre-training

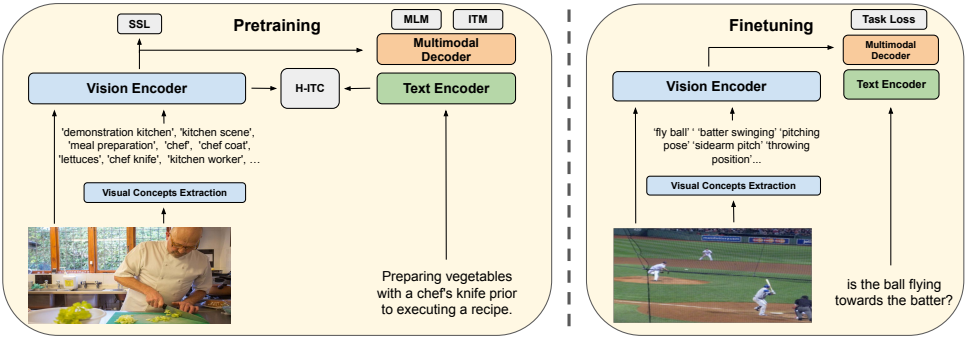

Figure 1: Illustration of our ViCHA approach; during pretraining (left) and finetuning (right).

dataset, Touvron et al. [71] obtained state-of-the art results using the same architecture with bag of learning recipes, without pre-training.

To this end, we propose a new VLP strategy with carefully designed training procedures and losses dedicated to efficiently align both modalities. Specifically, we adopt an early fusion architecture, but instead of having only one alignment loss on top of the dual encoders, we also align both representations at several layers. This hierarchical alignment strategy is extended with a multimodal fusion decoder in order to capture more complex Vision-Language interaction. We also exploit more efficiently the input data with Masked Image Modeling, based on the recently proposed Masked Auto Encoder (MAE) [26]. Moreover, we leverage image-level annotations (*i.e.*, objects and high level concepts describing the image) using existing foundation models (*i.e*, CLIP [55]) due their generalization ability and low computational cost at inference time. Thus departing from classical use of such models (*i.e.*, initialization and finetuning), and leveraging them without any retraining. We complete our scheme with a CLIP-based filtering technique. An illustration of our approach, called ViCHA for Efficient Vision-Language Pretraining with **Vi**sual **C**oncepts and **H**ierarchical **A**lignment, is presented in Fig. 1. We will show the effectiveness of our approach on classical downstream tasks used for VLP evaluation while drastically limiting the size of the training datasets, contrary to other methods.

2 Related Work

Vision and Language Pretraining (VLP): VLP methods can be categorized into 3 main categories based on their model architectures. First, dual stream approaches have two separate encoders for images and texts (e.g. CLIP [55], ALIGN [30]) that are usually trained using a contrastive loss [51] on a global similarity between their output embeddings. These models are efficient during inference, but can not exploit finegrained cross modal interaction that is useful for multimodal tasks (*e.g.*, VQA). Several attempts based on self supervision [41, 50], teacher-student distillation [3, 75] or finegrained interaction [82] have been proposed to alleviate the massive amount of data usually used for training (*e.g.*, CLIP 400M). Second, unified approaches try to simplify the model and adopt one transformer that can process the two modalities [73, 74]. These approaches are simpler, but still under perform other approaches with modality specific modules. Third, most of the work concentrated recently on hybrid approaches due to their success on multimodal tasks, where the models have separate encoders as well as a multimodal module that can exploit the cross-modal interaction more

effectively. Early methods have relied on object detection models to extract image regions and tags [12, 35, 37, 48, 66, 89], however, the visual representation is limited by the performance of the pretrained object detector, which is expensive to scale on large annotated datasets, besides being slow at inference time. To remedy this, many methods have proposed to replace the object detector with vision transformers [20, 32, 80] or CNNs [29, 77]. These models are usually trained with image-text matching (ITM [12]) or masked language modeling (MLM [18]) losses, and recently with image text contrastive (ITC) to align the vision and language representation before feeding them to the fusion module [22, 36, 81].

Multilevel Alignment: Using multiscale representation extracted from different stages of the model have shown to be successful for vision tasks, in particular, some work in representation learning have proposed to do contrastive learning [53] or mutual information maximization [5] between features extracted at different scales, or between local and global features [28]. In the context of VLP, Li et al. [42] propose a multilevel semantic alignment by aligning local and global representations. Gao et al. [24] propose an intra and cross level alignment based on features extracted from cropped images and image regions on one side, and the caption and its summarization on the other side. Li et al. [34] use both single and dual stream encoders to align the two modalities at multiple levels. Our approach use simpler strategy to align the features of both modalities at different transformer blocks.

Object tags: Several works have explicitly used high level concepts for vision-language tasks (*e.g.* for image captioning and VQA [79, 84]). In the context of VLP, the concepts are usually extracted from an off-the-shelf object detectors [58] which are fed to the multimodal transformer, alongside region features and text tokens [21]. Other than using object detectors, some approaches extract the concepts from the captions using Scene Graph Parser [2]. These concepts are used in several ways; predicting these concepts [47, 70, 85], using them as a bridge between non aligned image and text data [38], adopting a more efficient masking strategies [15] or leveraging them for fine-grained alignment [78]. In particular, OSCAR [40] uses the object tags to ease the alignment process by considering them as anchors for masked tokens prediction and contrastive learning. The concepts extracted from pretrained object detection models are limited to the training classes, in addition, scene graph parser are noisy and there is no guaranty that all the concepts in the caption are extracted. Our approach leverages a more general model to capture a large set of diverse concepts and using them to enhance the visual representation.

Leveraging Foundational Models: In recent years the focus have been shifted from task-customized models to more general or foundational models [55, 65, 87]. The motivation is to have a holistic model that can be later used or adapted to many downstream tasks. Due to their generalization capabilities, models such as CLIP [65], have been successfully leveraged in many tasks and domains, such as image editing [14], generation [57], segmentation [76], captioning [67], food retrieval [64], explainability [59] and beyond. In the context of VLP, these models are used as initialization [62] and recently, for dataset filtering [60]. In this work, we leveraged CLIP for the extraction of VCs and data selection/filtering.

3 ViCHA framework

Illustrated in Figure 2, our scheme presents Vision and Text encoders with three original components: a Visual Concepts Module to enrich the image encoder with relevant VCs, a new cross-modal interaction to align visual and langage feature representations at multiple levels, and a self-supervised component based on the recently proposed Masked Auto Encoder.

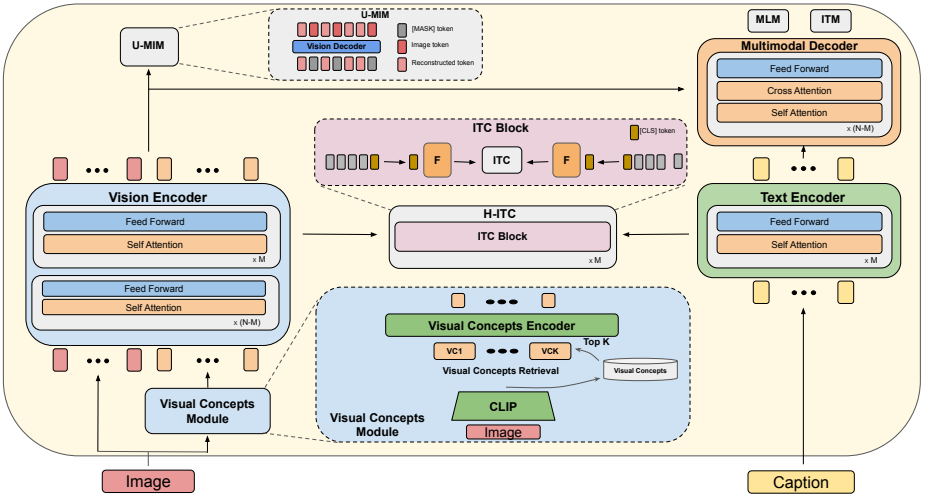

Figure 2: ViCHA framework: our Vision-Language transformer model consists of the vision encoder (left) and the text encoder (right), both aligned through our Hierarchical Image-Text Contrastive block (H-ITC). Importantly, the input visual tokens are completed through the Visual Concepts Module providing extra visual semantic tokens. Finally, a multimodal decoder (top right) allows to learn complex multimodal relationship thanks to MLM and ITM objectives. We also introduce a unimodal Masked Image Modeling (U-MIM) on top of the vision encoder.

Notations: Given a dataset of image-text pairs $\{I_i, T_i\}_i^K$, each image I_i is associated with several Visual Concepts (VCs) $\{C_i^1, ..., C_i^P\}$ extracted using CLIP and exploited by our vision encoder E_v. The VCs are projected to the image patches embedding space using a Visual Concept Encoder E_{vc}. E_v is a vision transformer that takes the image and the concepts as input and extracts the image tokens alongside a special class token $\{v_{cls}, v_1, ..., v_M\}$. Similarly, the text transformer encoder E_t takes the text or image caption T and extracts the text tokens $\{t_{cls}, t_1, ..., t_N\}$. The class tokens are aligned using a hierarchical contrastive loss before feeding the image and text tokens to a multimodal transformer decoder E_{vl} that takes the text tokens as query and the image ones as keys and values.

3.1 Enhancing Visual Representation with Visual Concepts

We propose to enhance the visual representation by explicitly injecting visual concepts. These concepts are extracted for each image, projected using a visual concepts encoder E_{vc} and then concatenated to the patch tokens before feeding them to the vision transformer E_v.

The motivation behind VCs is two-fold; VCs (a) might guide the vision encoder to focus on important objects/aspects of the image, (b) facilitate the alignment with the textual modality, first, because the visual tokens are already fused with the textual tokens of the VCs, second, it is easier to align the caption/text with the VCs tokens than the image tokens, especially at the beginning of the training.

Also we can see this technique from a visual prompt perspective. Text prompts are usually used with large language models to steer their output based on a given task/input [8, 44, 53, 83]. We derive the analogy between these prompts and the prepend of VCs, as they may also guide the model to focus on different aspects of the image during training.

Next, we detail how we extract, project and incorporate the VCs in our framework;

Visual Concepts Extraction: Different from other approaches (*e.g.*, OSCAR [40]) that extract these concepts (*i.e.*, object tags) using pretrained object detectors, we use an off-the-shelf foundational model to extract more diverse, larger and semantically meaningful set of visual concepts. We show in section 4, that this approach helps to capture high level and global concepts describing the scenes, which are hard to obtain with other approaches (*e.g.* object detectors). The extraction of the visual concepts is done as follows;

1. Concepts extraction: we extract the objects using Scene Graph Parsers [61] from all the captions of a given dataset. We use only simple text filters (transform to lower case and select objects repeated more than once). However, more complicated filters might improve the results even further.

2. Concepts and image embeddings: We use a pretrained CLIP (ViT-B/16) model to obtain the embeddings of all the images and the extracted concepts.

3. Concepts selection: for each image, we compute its cosine similarity with all the embedded concepts and select the top k similar concepts.

Visual Concepts Encoder (E_{vc}): To encode Visual Concepts, we use a small text encoder E_{vc} and then concatenate the output token embeddings with the image patch tokens before feeding E_v.

Visual Concepts Augmentation (VCA): Here we propose a simple yet effective VCs augmentation technique. Having a set of concepts extracted for each image, instead of considering all the concepts at once, we sample randomly a fraction of these concepts (*i.e.*, $p_{vc}\%$) at each iteration step. The benefit of VCA is three-fold; (1) it may prevent the model from overfitting on specific concepts and potentially disregard the image or other concepts during training, (2) the model sees different combinations of concepts, which helps to have more diversity. (3) the model is exposed to more information during finetuning or test, as it will see all the concepts at once.

3.2 Training scheme

We pretrain the model using several objectives; Hierarchical Image-Text Contrastive Learning (H-ITC), ITM, MLM and Masked Image Modeling (MIM).

Hierarchical Image-Text Contrastive Learning (H-ITC) Here we propose to exploit the hierarhical representations capture by the vision and language encoders. CNN based vision encoders learn hierarchical representations, starting from local features to more abstract ones at later stages [88]. Vision transformers have also been shown to display some level of hierarchy in learned representations [19, 56].

On the text side, recent works show that the attention heads specialize in particular part-of-speech tags, which differs across heads and layers [72] and reflect different aspects of the syntax [13], while the concepts learned by BERT differ significantly across layers and evolve into representing a linguistic hierarchy [16].

Motivated by this, and different from other work [22, 36, 81] that align the two modalities only at the last layer, we propose to align them at different layers of the vision and text transformers. We argue that doing the alignment at early stages facilitates the process at the subsequent layers, while allowing to align the representation at different semantic levels.

There is an asymmetry between the visual and textual information, as the image contains more diverse and detailed information while the caption usually contains more abstract one, thus we align the textual features only with the visual ones from the last layers of E_v.

Method	# Pre-train Images	VQA		NLVR^2		SNLI-VE	
		test-dev	test-std	dev	test-P	val	test
ViLBERT [18]	3M	70.55	70.92	-	-	-	-
12-in-1 [19]	3M	73.15	-	-	78.87	-	76.95
ERNIE-ViL [33]	3.8M	73.18	73.36	-	-	-	-
ImageBERT [34]	6M	-	-	-	-	-	-
Unicoder-VL [35]	3.8M	-	-	-	-	-	-
UNITER [4]	4M	72.70	72.91	77.18	77.85	78.59	78.28
OSCAR [10]	4M	73.16	73.44	78.07	78.36	-	-
VILLA [7]	4M	73.59	73.67	78.39	79.30	79.47	79.03
UNIMO$_B$ [39]	4M+1.7M	73.79	74.02	-	-	80.00	79.10
ViLT [31]	4M	70.94	-	75.24	76.21	-	-
ALBEF [26]	4M	74.54	74.70	80.24	80.50	80.14	80.30
ALBEF*	1.1M	72.51	72.69	75.72	76.31	78.08	78.02
ViCHA	1.1M	**73.55**	**73.52**	**77.27**	**77.08**	**78.96**	**78.22**
ViCHA†	800K	73.23	-	78.14	77.00	79.02	78.65

Table 1: Comparison with SOTA; we report the accuracy on VQA, NLVR^2 and VE. ViCHA outperforms other approaches trained on much more data ($\sim$ 4M images) and SOTA trained on the same setup (ALBEF*). Our model trained on the filtered dataset (ViCHA†) is very competitive while using much less data ($\sim$ 800K images). Results on 4M images are in the supp.

Specifically, at layer i, we compute the image-to-text and text-to-image similarities and then apply a Softmax with a learned temperature parameter τ:

$$p^i_{i2t} = \frac{exp(s(I,T)^i/\tau)}{\sum_{m=1}^{Q} exp(s(I,T_m)^i/\tau)}, \quad p^i_{t2i} = \frac{exp(s(T,I)^i/\tau)}{\sum_{m=1}^{Q} exp(s(T,I_m)^i/\tau)}, \tag{1}$$

T_m and I_m are the negative text and image examples. $s(\cdot,\cdot)^i$ is the cosine similarity and is obtained after linearly projecting and normalizing the class tokens at layer i into a shared latent space:

$$s(I,T)^i = g_{vi}(v^i_{cls})^T g'_{ti}(t^i_{cls}), \quad s(T,I)^i = g_{ti}(t^i_{cls})^T g'_{vi}(v^i_{cls}), \tag{2}$$

where $g_{ti}()$ and $g_{vi}()$ are the linear projection layers at layer i. We maintain two queues of size Q that store the normalized features from the momentum models $g'_{li}()$ and $g'_{vi}()$. We didn't see a significant improvement when using queues for the other layers, thus we use the queues only for the last layer for simplicity (on select in-batch negative examples for other layers). We then compute the cross entropy loss between $\boldsymbol{p}$ and the one-hot ground truth and sum across all layers.

Image-Text Matching (ITM) ITM loss is applied on top of the multimodal trasformer decoder for more finegrained fusion. It is a binary cross entropy loss, where the model tries to classify if the image-text pairs are positive or negative. The image and its corresponding caption are considered as positive pairs while the other examples in the batch are considered as negative. We sample a hard text and hard image from the batch based on the global cosine similarity on top of the dual encoders [36].

Masked Language Modeling (MLM) MLM consists of predicting a masked token given other contextual tokens. In our work, the model has also access to the visual tokens, which helps to learn a cross modal representation. Following BERT [18], we mask 15% of the tokens and replace them with [MASK] token, random token or we keep them unchanged with probabilities of 80%, 10% and 10% respectively. The task is a classification loss where the model should predict the token id from a list of vocabulary.

Method	# Pre-train Images	Flickr30K (1K test set)						MSCOCO (5K test set)					
		TR			IR			TR			IR		
		R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
ViLBERT [43]	3M	-	-	-	58.2	84.9	91.5	-	-	-	-	-	-
12-in-1 [42]	3M	-	-	-	67.90	-	-	-	-	-	68.00	-	-
ERNIE-ViL [53]	3.8M	86.7	97.80	99.00	74.44	92.72	95.54	-	-	-	-	-	-
ImageBERT [34]	6M	87.0	97.6	99.2	73.1	92.6	96.0	66.4	89.8	94.4	50.5	78.7	87.1
Unicoder-VL [25]	3.8M	-	-	-	-	-	-	62.3	87.1	92.8	46.7	76.0	85.3
UNITER [4]	4M	87.3	98.0	99.2	75.6	94.1	96.8	65.7	88.6	93.8	52.9	79.9	88.0
OSCAR [41]	4M	-	-	-	-	-	-	70.0	91.1	95.5	54.0	80.8	88.5
VILLA [14]	4M	87.9	97.5	98.8	76.3	94.2	96.8	-	-	-	-	-	-
UNIMO$_B$ [39]	4M+1.7M	89.7	98.4	99.1	74.7	93.4	96.1	-	-	-	-	-	-
ViLT [24]	4M	83.5	96.7	98.6	64.4	88.7	93.8	61.5	86.3	92.7	42.7	72.9	83.1
ALBEF [32]	4M	94.3	99.4	99.8	82.8	96.7	98.4	73.1	91.4	96.0	56.8	81.5	89.2
ALBEF*	1.1M	88.1	97.8	99.0	73.6	92.0	95.6	71.2	91.3	95.6	54.2	80.7	88.6
ViCHA	1.1M	**91.7**	**98.7**	**99.5**	**77.2**	**94.2**	**96.8**	**73.6**	**92.4**	**96.2**	**56.8**	**82.2**	**89.5**
ViCHA†	800K	90.0	98.4	99.8	77.4	94.3	96.7	73.3	92.1	96.2	55.8	81.8	89.1

Table 2: Comparison with SOTA; we report R@K for finetuning on Image-Text Retrieval. ViCHA outperforms other approaches trained on much more data ($\sim$ 4M images) and SOTA trained on the same setup (ALBEF*). Our model trained on the filtered dataset (ViCHA†) is very competitive while using much less data ($\sim$ 800K images). Results on 4M images are in the supp.

Masked Image Modeling (MIM): Improving the visual representation have shown to affect significantly the performance on vision-language tasks [8, 9]. Many work in self supervised learning (SSL) have been proposed [9, 25], in particular, the methods based on masked image reconstruction have achieved SOTA results [6, 26]. However, it is not clear how much MIM is useful for VLP, as recent work show that MIM based on approaches such as BEiT, masked region regression or classification degrades the performance [20, 27, 32]. Motivated by these findings, here we propose two approaches to investigate whether MIM could help VLP. The two methods are based on the recent Masked Auto Encoder (MAE) approach [26], where we randomly mask the image (*e.g.*, 75%) and pass only the unmasked tokens to E_v, however, they are different in how they reconstruct the image:

Unimodal MIM (U-MIM): Here we propose to improve the visual representation by reconstructing the masked tokens given only the unmasked image ones (without access to VCs). Specifically, we add a small decoder D_v (*e.g.*, 2-layer transformer) that takes the output tokens, concatenated to the masked ones ($\hat{\boldsymbol{v}}$) and reconstruct the input image as $\hat{I}$. The unimodal masked image modeling (U-MIM) loss can be written as:

$$\mathcal{L}_{U-MIM} = MSE(I, D_v(\hat{\boldsymbol{v}})). \tag{3}$$

Multimodal MIM (M-MIM): Here the decoder has access also to the textual tokens, which helps to provide more informative context to reconstruct the masked tokens. The decoder is the same as our E_{vl} (shared weights) but is provided with the visual tokens ($\hat{\boldsymbol{v}}$) as queries and the textual ones ($\boldsymbol{t}$) as keys and values (hence, the queries, keys and values are different when computing MLM and ITM). The loss can be written as:

$$\mathcal{L}_{M-MIM} = MSE(I, F(E_{vl}(\hat{\boldsymbol{v}}, \boldsymbol{t}))), \tag{4}$$

where F is a linear projection. The total loss can be written as ($\lambda_{H-ITC} = 0.1$ and $\lambda_{MIM} = 1$):

$$\mathcal{L} = \mathcal{L}_{ITM} + \mathcal{L}_{MLM} + \lambda_{H-ITC}\mathcal{L}_{H-ITC} + \lambda_{MIM}\mathcal{L}_{MIM}. \tag{5}$$

4 Experiments

We follow other works [36] and evaluate the model on four downstream tasks: Image-Text Retrieval, VQA, NLVR^2, Visual Entailment and Visual Grounding. More details about

Method	# Pre-train Images	Flickr30K (1K test set)						MSCOCO (5K test set)					
		TR			IR			TR			IR		
		R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
ImageBERT [30]	6M	70.7	90.2	94.0	54.3	79.6	87.5	44.0	71.2	80.4	32.3	59.0	70.2
UNITER [4]	4M	80.7	95.7	98.0	66.2	88.4	92.9	-	-	-	-	-	-
ViLT [24]	4M	73.2	93.6	96.5	55.0	82.5	89.8	56.5	82.6	89.6	40.4	70.0	81.1
ALBEF [36]	4M	90.5	98.8	99.7	76.8	93.7	96.7	68.7	89.5	94.7	50.1	76.4	84.5
CLIP [43]	400M	88.0	98.7	99.4	68.7	90.6	95.2	58.4	81.5	88.1	37.8	62.4	72.2
ALIGN [20]	1.2B	88.6	98.7	99.7	75.7	93.8	96.8	58.6	83.0	89.7	45.6	69.8	78.6
ALBEF*	1.1M	81.3	94.9	98.2	64.7	87.2	92.0	59.5	84.4	91.2	38.3	68.0	79.1
ViCHA	1.1M	**86.0**	**97.1**	**99.0**	**72.6**	**91.1**	**95.0**	**63.1**	**86.9**	**92.7**	**47.1**	**73.8**	**82.8**
ViCHA†	800K	85.0	96.8	98.7	71.6	91.0	94.9	-	-	-	-	-	-

Table 3: Zero-shot Comparison with SOTA on Flickr30K (after fine-tuning ViCHA on COCO) and COCO (pretrained model only).

downstream tasks, implementation details, comparability and dataset filtering can be found in the Appendix.

Our setup: We favor low data and compute regimes. Specifically, we pretrain only on 3 public datasets; COCO [43], Visual Genome [33] and SBU [52], which account to $\sim 1.1M$ images in total, thus, 4 times lower than other approaches (*e.g.* 4M images [12, 20, 36]). In addition, we train for 10 epochs (in contrast to 30 epochs [22, 36, 81]) with relatively small batch size of 128 (32 per GPU) using 4 GPUs.

Filtered dataset: We go further and apply a CLIP-based filtering technique to reduce the number of images to $\sim 800k$, and train our approach on this dataset (ViCHA†). This dataset consists of; COCO, 50% of VG captions and 70 % of SBU.

Implementation details: We follow the implementation of ALBEF [36], including the same architecture, with our setup. The visual encoder is ViT-B/16 [19, 71], the text encoder is the first 6 layers of BERT-base [18] and the multimodal encoder is the last 6 layers of BERT-base. E_{vc} is the first 2 layers of BERT-base. We extract 15 concepts for each image and we set p_{vc}=30% for VCA. For H-ITC loss, we use the last 6 layers of E_v and the all 6 layers of E_l. For U-MIM, we use 2-layer transformer encoder.

To have a fair comparison, we compare with ALBEF trained on the same setup (called ALBEF*). Even though it is common to compare among all approaches in the literature, we think that it is hard to assess the methods as they follow different training setups.

Comparison with SOTA on standard tasks: Table 1 shows a comparison with other approaches, on *VQA, NLVR^2, VE* following the finetuning setup. We outperform significantly ALBEF* (+1.04% VQA, +1.55% NLVR^2 and +0.88% VE) and other approaches trained on more data (*i.e.*, 4M images), such as ViLT (+2.61% VQA, +2.03% NLVR^2), UNITER (+0.85% VQA, and +0.37% VE) and OSCAR (+0.39% VQA). For *Image-Text Retrieval*, The model is evaluated on COCO and Flickr30K (F30K) following 2 setups; finetuning and zero-shot. Table 2 shows the finetuning results. Compared to ALBEF*, our approach achieves significant improvements, especially on R@1 with absolute improvement of 3.74% IR and 3.6% TR on Flickr30K, and 2.59% IR and 2.42% TR on the more challenging COCO. Interestingly, we outperform other approaches trained on more data such as ViLT, UNITER and UNIMO (+2.58% R@1 IR F30K). Compared to the SOTA trained with 4M images, we outperform ALBEF [36] on COCO (+1.72% TR RSUM and +0.88% IR RSUM). On zero-shot F30K, we follow other approaches [22, 36, 81] and use the model finetuned on COCO. While for zero-shot COCO, we directly use the model after pretraining (without VCA). Note that, by zero-shot, we mean the model is not explicitly trained on the target dataset after pretraining.

VCs	H-ITC	U-MIM	VCA	Flickr30K (1K test set) RSUM	TR R@1	TR R@5	TR R@10	IR R@1	IR R@5	IR R@10	VQA test-dev Acc.
Baseline (ALBEF*)				535.8	85.8	97.4	98.5	70.2	89.9	94.0	71.1
✓				545.4	87.6	97.6	99.3	74.0	91.6	95.3	71.6
	✓			545.1	87.3	98.1	99.3	73.2	92.0	95.2	72.0
		✓		543.6	88.6	97.6	99.2	72.3	91.1	94.8	71.8
✓	✓			547.6	88.3	97.6	99.3	73.7	92.7	96.0	71.8
✓	✓	✓		550.0	89.8	97.6	99.3	74.9	92.8	95.6	71.7
✓	✓	✓	✓	550.7	88.2	97.8	99.4	75.7	93.4	96.2	72.6

Table 4: Ablation study: The models are finetuned on Flickr30K and VQA v2 (as in [20, 31]).

Table 3 shows that our model significantly outperforms ALBEF* (+7.88% F30K and +8.76% COCO R@1 IR) and other approaches trained on more data such as UNITER, ViLT, CLIP on F30K IR and COCO, as well as ALIGN on COCO.

Ablation Study: Table 4 shows the contribution of the different components of our ViCHA strategy. Using VCs seems to give significant improvements over the baseline (+9.6% RSUM and +0.5% Acc. VQA), similarly for H-ITC and MIM. Then we add our H-ITC loss, which also brings additional points (+2.2% RSUM and +0.2% Acc. VQA), showing the importance of a stronger pre-alignment loss. We favor the MAE based, unimodal MIM loss which improves the results by 2.4% RSUM. We choose U-MIM over M-MIM due to its superior performance, however, both objectives gives better result than the baseline; +7.8% and +3.2% RSUM for U-MIM and M-MIM respectively (detailed results can be found in the appendix). This reveals the importance of MIM as well as using SSL objectives for VLP. We finally add VCA, that significantly help the VQA task (+0.9% Acc.). Overall, we show that all contributions are not antagonistic and can be combined effectively. More ablation can be found in the appendix.

Data and Compute Efficiency: The way the VCs are extracted (using CLIP) is not central to our work, as for the gain coming from 400M pairs of CLIP. This is supported in our experiments in the supplementary material, where we replace CLIP by an object detector. In addition, Table 4 shows that other components contribute significantly, where the gain coming from H-ITC and U-MIM individually, is comparable to VCs. The number of params of ViCHA during inference is 248.5 M compared to 209.9 M for ALBEF and $\sim$ 265 M for METER [20]. The training time of ViCHA (1M) is $\sim$ 70 hours, for ViCHA (800K) the training time is much lower (39h). This is with the paper setup (4 GPUs A100). Compared to other SOTA, using 8GPUs A100; ALBEF [36] takes 2-3 days and METER 8 days [20].

Additional Scores on Visual Grounding: Table 5 shows a comparison between Weakly Supervised Visual Grounding (WSVG) approaches on the RefCOCO+ dataset. We outperform ALBEF* (+0.67 % val, +1.06 % TestA and + 1.19 % TestB) as well other approaches such as DTMR Sun et al. [59] and KPRN Liu et al. [46]. Compared to ALBEF trained on 4M images we obtain better performance on the TestA set (+ 0.68 %). In addition, we show some qualitative results using Grad-CAM by back propagating the ITM loss until the 3rd layer of the multimodal encoder, the results can be found in the appendix.

Data filtering: Interestingly, the model trained on the filtered data (ViCHA†) gives comparable results on image-text retrieval (Table 2 and 3), sometimes better than, training on all data (*e.g.*, NLVR^2 and SNLI-VE, Table 1), while being always better than ALBEF*.

Illustration of VCs: We show (Figure 3) that VCs can capture high level, global and some aspects in the scene that can not be shown explicitly or detected by other techniques (*e.g.*,

Method	Val	TestA	TestB
ARN [25]	32.78	34.35	32.13
CCL [21]	34.29	36.91	33.56
KPRN [44]	35.96	35.24	36.96
DTMR [53]	39.18	40.01	38.08
ALBEF [32]	58.46	65.89	46.25
ALBEF*	57.00	65.51	44.24
ViCHA	57.67	66.57	45.63
ViCHA†	56.40	65.93	45.69

Table 5: Comparison with SOTA on Weakly Supervised Visual Grounding RefCOCO+.

Object detectors as in OSCAR [40]).

Dataset: COCO
Caption: "Prepping vegetables with a chef's knife prior to executing a recipe."
VCs: 'demonstration kitchen', 'cooking demonstration', 'kitchen restaurant scene', 'galley kitchen', 'kitchen scene', 'type kitchen', 'meal preparation', 'food preparation', 'chef', 'chef coat', 'lettuces', 'chef knife', 'efficiency kitchen', 'plan kitchen', 'kitchen worker'

Dataset: SBU
Caption: ' Mom opening up a bottle of cider mix from Catherine. Stupid tree was in my way.'
VCs: 'santa juana', 'mama santa', 'bev pelletier', 'pam tree', 'amazon', 'sue veeder', 'christmaspresents', 'christmas woman', 'christmas basket', 'anne peterson', 'santa gifts', 'holiday cheer', 'pamela hinshaw', 'cynthia rybakoff', 'christmas'

Dataset: VG
Caption: 'the hat is pink'
VCs:'birthday celebrate', 'birthday celebration', 'birthday party', 'cake cutting', 'celebration cake', 'cake portion', 'birthay cake', 'bithday cake', 'child cake', 'birth day', 'celebration', 'cutting cake', 'birthday', 'congratulations cake', 'birthday cake'

Figure 3: Illustration of VCs: VCs capture global information, actions and other aspects of the scene that help to give a rich context.

5 Conclusion

We propose a new efficient VLP approach centered on 3 main components; stronger Vision-Language pre-alignment through hierarchical contrastive objective, self supervision via masked image modeling based on MAE, and a new Visual Concepts injection and extraction technique. The approach outperforms state of the models trained on the same setup (+3.6% F30K TR and +1.04 Acc. VQA compared to ALBEF), as well as others trained on much more data (times 4 more data, such as OSCAR and ViLT). Overall, we show that investing in the learning schemes is a very promising approach that helps to exploit more effectively the data, especially at low data regime. We hope that this work will encourage more effort (from a wider range of research laboratories) in this direction, that might lead to have more mature techniques, and then, perhaps, wisely leverage them when going large scale.

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