Vision-Language Models Do *Not* Understand Negation

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Abstract

Many practical vision-language applications require models that understand negation*, e.g., when using natural language to retrieve images which contain certain objects but not others. Despite advancements in vision-language models (VLMs) through large-scale training, their ability to comprehend negation remains underexplored. This study addresses the question: how well do current VLMs understand negation? We introduce NegBench, a new benchmark designed to evaluate negation understanding across 18 task variations and 79k examples spanning image, video, and medical datasets. The benchmark consists of two core tasks designed to evaluate negation understanding in diverse multimodal settings: Retrieval with Negation and Multiple Choice Questions with Negated Captions. Our evaluation reveals that modern VLMs struggle significantly with negation, often performing at chance level. To address these shortcomings, we explore a data-centric approach wherein we finetune CLIP models on a large-scale synthetic datasets containing millions of negated captions. We show that this approach can result in a 10% increase in recall on negated queries and a 40% boost in accuracy on multiple-choice questions with negated captions.*

1. Introduction

Joint embedding-based Vision-Language Models (VLMs), such as CLIP, have revolutionized how we approach multimodal tasks by learning a shared embedding space where both images and text are mapped together. This shared space enables a variety of applications, including cross-modal retrieval, video retrieval, text-to-image generation, image captioning, and even medical diagnosis (CITE[?]). By aligning visual and linguistic representations, these models achieve remarkable performance across domains and are able to model complex interactions between vision and language inputs.

Despite these advances, there is an emerging limitation: these models often fail to handle *negation*, which is essential in many real-world scenarios. Negation allows users to specify what is absent or false, such as when aradiologist is searching for images showing "bilateral consolidation with no evidence of pneumonia" or a safety inspector querying "construction sites with no barriers"(CITE[?]). Current benchmarks like CREPE and CC-Neg have introduced some forms of negation, but they rely on rigid, templated examples that do not reflect the complexity of natural language queries (CITE[?]). As a result, these benchmarks fall short in evaluating how well VLMs understand negation in practical applications.

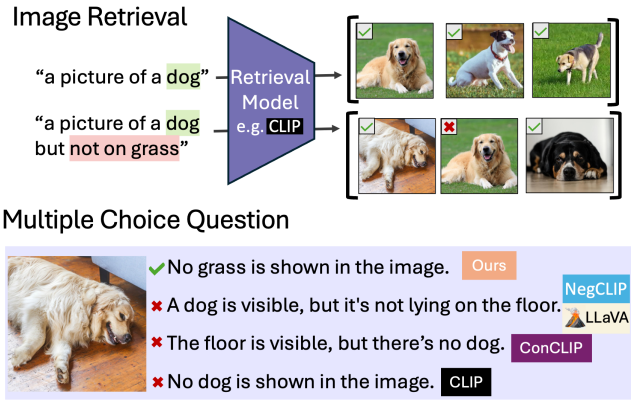

Figure 1. **Can Vision-Language Models Understand Negation?**

To comprehensively evaluate how well VLMs handle negation, we adopt a Two-Stage Evaluation Pipeline. Our pipeline mirrors real-world information retrieval systems, where a coarse-grained retrieval step is followed by a fine-grained ranking or selection step [20, 24].

The first stage, Retrieval-Neg, tests whether models can handle real-world queries that mix affirmative and negative statements, such as "a beach with no people" or "a building without windows." This task challenges the model to retrieve images from diverse datasets based on the presence of certain elements and the absence of others, simulating scenarios found in search engines, content moderation, and recommendation systems. By retrieving several potentially relevant matches (e.g., top-5 retrieval), Retrieval-Neg serves as the coarse-grained retrieval step in our pipeline.

The second stage, MCQ-Neg, provides a fine-grained,

structured evaluation that directly assesses specific failures in negation. In this task, the model must choose the correct description of an image from several closely related options, where the incorrect choices are hard negatives, differing only by what is affirmed or negated. For instance, in medical diagnostics, consider distinguishing between "The X-ray shows evidence of pneumonia but no evidence of pleural effusion" and "The X-ray shows evidence of pleural effusion but no evidence of pneumonia." These statements are linguistically similar but convey opposite diagnoses, requiring the model to parse subtle yet critical differences.

Through our evaluation pipeline, we uncover a surprising limitation: joint embedding-based VLMs frequently collapse affirmative and negated statements into similar embeddings, treating "a dog" and "no dog" as nearly indistinguishable. This affirmation bias reveals a significant shortcoming that was not sufficiently addressed in previous benchmarks like CREPE or CC-Neg.

Recognizing this critical gap, we then ask: If current models fail to understand negation, can we improve them? To tackle this, we propose a data-centric solution, introducing two large-scale synthetic datasets—Syn-Neg-Cap and Syn-Neg-MCQ—designed to improve negation comprehension. Fine-tuning CLIP on these datasets leads to substantial improvements, including a 10% increase in recall on negated queries and a 40% boost in accuracy on multiple-choice questions with negated captions.

Through NegBench, a systematic error analysis, and a targeted data-driven solution, our work provides a structured approach to understanding and addressing the challenges of negation in VLMs. We will open-source all models and data, hoping to inspire broader research in negation understanding and its wide-ranging applications.

2. Related Work

Our work lies within the field of evaluating and advancing foundational vision-language models (VLMs). Joint-embedding models based on CLIP [26] show impressive generalization across visio-linguistic tasks like cross-modal retrieval, image captioning, and visual question answering [2, 15, 16, 25, 27, 30, 33–35] in diverse visual domains, extending beyond natural images to videos and medical images [3, 11, 18, 19, 23, 43]. We introduce a benchmark and data-centric approach to rigorously evaluate and improve negation understanding in these VLMs.

Negation Understanding in Language and Vision. Recent work showed that large language models perform suboptimally when tasked with negation understanding [8]. We go a step further by showing that vision-language models exhibit a more severe affirmation bias, completely failing to differentiate affirmative from negative captions.

Despite this critical limitation, existing benchmarks provide limited assessments of negation in VLMs. CREPE [21] and the concurrent work CC-Neg [36] are among the few vision-language benchmarks that include negation, but they focus on compositional understanding and rely on linguistic templates that fail to reflect the varied ways negation appears in real user queries. In contrast, our proposed benchmark, NegBench, leverages an LLM to generate natural-sounding negated captions, spanning a broader range of negation types and contexts across images, videos, and medical datasets. This systematic design enables a thorough evaluation of VLMs' ability to handle negation in multimodal settings, uncovering unique challenges and failure cases that have not been fully addressed in prior work.

Improving CLIP for Compositionality and Negation. Recent methods have explored improving the generalization abilities of CLIP-like VLMs for visio-linguistic compositionality and limited aspects of negation understanding. For instance, NegCLIP [42] employs composition-aware mining when finetuning CLIP to enhance compositional reasoning, while ConCLIP [36] modifies the CLIP loss to incorporate synthetic, template-based negation examples. In the medical domain, negation is a common feature in clinical text reports, often indicating the absence of specific pathologies [39]. Specialized models like BiomedCLIP [43] and CONCH [18] have been pretrained on millions of biomedical image-text pairs to address a variety of medical tasks, leveraging domain-specific knowledge from large-scale multimodal data. NegBench provides a systematic way to evaluate general-purpose and medical VLMs.

Synthetic Data for Model Training. It is common to use synthetic data to improve the performance of models in computer vision [1, 5, 13, 41]. Recent studies have shown that it is possible to use synthetic data to learn general vision-language representations, with some models trained entirely on synthetic images and captions achieving results comparable to real data [10, 37, 38]. Our approach is similar in spirit, but it constructs synthetic datasets to teach models a new, complex capability—*negation understanding*.

3. The Negation Benchmark (NegBench)

We design NegBench as a two-stage pipeline to evaluate the capacity of joint-based vision-language models to understand negation. This structure mirrors real-world applications where an initial, broad retrieval phase is followed by a precise selection or ranking phase.

In the Retrieval-Neg stage, we assess models on their ability to process real-world queries that blend affirmative and negative statements, simulating search tasks where users specify the presence of some elements and the absence of others. The task challenges models to retrieve a set of relevant images (e.g., top-5) that meet these mixed conditions. The second stage, MCQ-Neg, further evaluates models' understanding of negation by having them select the correct description of an image from options that differ only in the

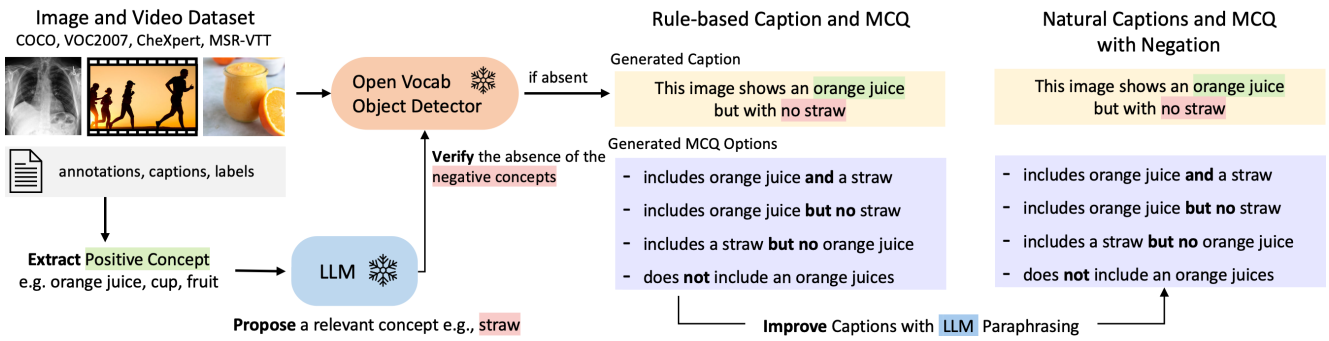

Figure 2. **General Pipeline for Constructing NegBench**

affirmation or negation of specific elements.

3.1. Transforming Datasets for Negation Evaluation

General Dataset Transformation Overview. To implement the two-stage evaluation pipeline of NegBench, we adapt several popular vision datasets, covering images (COCO [17], VOC2007), video (MSR-VTT [40]), and specialized medical imaging domains (CheXpert [12]). For each dataset, we identify positive elements $\{pos\}$, which represent objects or concepts present in the image, and negative elements $\{neg\}$, which are absent from the image but commonly associated with the present objects. When available, we use object-level annotations to identify these elements, as in COCO, VOC2007, and CheXpert; for other datasets, we derive positive and negative elements directly from the captions. This flexible approach allows NegBench to extend any vision dataset, whether it includes object-level annotations or captions, to evaluate negation comprehension across diverse tasks and data modalities.

In the Retrieval-Neg task, we modify standard captions by including negations, evaluating how models handle queries that specify both present and absent elements. For example, captions are modified as: "There is no x in the image. [Original Caption]." or "[Original Caption]. There is no x in the image." To introduce linguistic diversity, we use LLaMA 3.1 [6] to paraphrase these captions.

For the MCQ-Neg task, we generate multiple-choice questions (MCQs) for each image. The model must identify the correct description based on three linguistic templates: Affirmation, Negation, and Hybrid [14].

1. Affirmation: "This image includes **A** (and **C**)."
2. Negation: "This image does not include **B**."
3. Hybrid: "This image includes **A** but not **B**."

Each MCQ consists of one correct answer and three incorrect answers, which serve as hard negatives, misleading the model if it does not properly understand negation. A correct answer accurately describes the presence of $\{pos\}$ elements or negates $\{neg\}$ elements. A False Affirmation (e.g., "This image includes x" when $x \in \{neg\}$) or a False Negation (e.g., "This image does not include x" when $x \in \{pos\}$) highlights the model's failure to comprehend the image. The Hybrid template further evaluates the model's ability to combine affirmation and negation in the same caption. These MCQs are also paraphrased using LLaMA 3.1 to increase linguistic diversity.

3.2. Applicability Across Data Types and Domains

NegBench supports a wide range of data types and domains, enabling comprehensive negation evaluation.

Video Understanding. Video retrieval tasks introduce temporal complexity, where negation can involve both objects and actions that vary over time. Using MSR-VTT as an example, we prompt LLaMA 3.1 [6] to extract positive and negative elements from each video's caption. These elements may represent either objects present in the video or actions taking place. For Retrieval-Neg, we create captions specifying both the presence of some elements and the absence of others (e.g., "A person is cooking but not eating"). In MCQ-Neg, we generate multiple-choice questions where the model must select the description that most accurately represents a video segment, requiring it to reason about negation of objects and actions in dynamic scenes.

Medical Image Interpretation with CheXpert. Accurate negation understanding is critical in high-stakes domains like medical imaging. Using the CheXpert dataset [12], we focus on the most frequent condition *Lung Opacity* and design two binary classification tasks:
Task 1: Affirmation Control Task. This task evaluates the model's ability to associate images with specific medical conditions using affirmative statements.

Question: Which option describes this image?
A) This image shows Lung Opacity.
B) This image shows Atelectasis.

Task 2: Negation Understanding Task. This task tests whether the model can correctly interpret negation, distinguishing the presence or absence of a medical condition.

Question: Which option best describes the image?

A) This image shows Lung Opacity.
B) This image does *not* show Lung Opacity.

These extensions highlight the adaptability of NegBench to various data types and domains, from general images and videos to specialized medical imaging. This versatility ensures that NegBench provides rigorous, contextually relevant evaluations of negation understanding in VLMs.

3.3. Synthetic Datasets for Controlled Evaluation

To rigorously test negation understanding, we construct datasets that precisely control object presence and absence.

Motivation and Benefits of Synthetic Data. Synthetic data offers several advantages over traditional image datasets. First, by creating "hard negatives"—image pairs that differ only by a single object's presence or absence—we can evaluate the sensitivity of models to negation with minimal confounding variables. Additionally, image datasets like COCO and VOC2007 are limited in the range of visual concepts they cover; COCO has 80 objects while VOC2007 includes only 20. To expand this diversity, we prompt a large language model to propose a broader set of objects, which we use as targets in our synthetic dataset. This approach enables the generation of visually varied scenes that more comprehensively test negation comprehension across a wider array of objects and contexts.

Construction Process for Synthetic Negation Dataset. We create 10,000 image pairs using Stable Diffusion [29], where each pair includes one image containing a target object and another where it is explicitly absent. To ensure accurate object presence or absence, we use the open-vocabulary object detector OWL-ViT [22].

4. NegBench Evaluations: Results and Insights

In this section, we benchmark the negation abilities of different VLMs using NegBench, comparing models based on their architecture, training data, and training objectives to reveal specific areas where negation understanding remains limited. Specifically, we evaluate five CLIP ViT-B/32 models on Retrieval-Neg and MCQ-Neg tasks. These include OpenAI CLIP [26], CLIP-laion400m [32], and CLIP-datacomp [7], which differ by pretraining dataset, as well as NegCLIP [42], trained to improve compositional language understanding, and ConCLIP [36], trained specifically to improve negation understanding. To handle the video dataset, MSR-VTT, we follow [3] and encode 4 uniformly sampled frames per video, averaging their features to obtain the CLIP video embedding. For medical tasks, we evaluate CONCH [18] and BioMedCLIP [43], two medical foundation VLMs. We also assess the impact of scaling up CLIP (ViT-B, ViT-L, and ViT-H) to determine if model size improves negation understanding.

CLIP models struggle with negated queries in retrieval tasks. We evaluate five CLIP-based models on the original COCO text-to-image retrieval task and its Retrieval-Neg version, where captions include negated statements. Across models, performance drops significantly on the negated task. In COCO retrieval (Figure 3a), CLIP-laion400m experiences a 7.7% drop in recall@5, with CLIP-datacomp and NegCLIP showing drops of 7.6% and 6.8%, respectively. In the more challenging SD-Neg retrieval task (Figure 3b), the performance drops are even more pronounced due to the presence of hard negatives, *i.e*. images that closely resemble positive examples but differ by the exclusion of a single object. Here, NegCLIP, despite its promise for compositional understanding, suffers a 23.0% drop, while ConCLIP, designed specifically for negation understanding, still declines by 18.0%. These results suggest that interpreting negation, particularly in the presence of hard negatives, remains a key challenge for retrieval tasks.

MCQ-Neg reveals severe limitations in CLIP models. Figure 4a shows that most models perform worse than random guessing (indicated by the red dashed line at 25%) on the MCQ-Neg task, with CLIP-base achieving only 15% on COCO and 8% on VOC2007. These results reveal a fundamental limitation of CLIP's pretraining objective, which encourages strong associations between visual concepts and specific words, but struggles to interpret negation. Notably, CLIP-laion400m performs better, reaching over 40% accuracy on the SYNTHETIC dataset. This improvement likely stems from the fact that both CLIP-laion400m and Stable Diffusion (used to generate the SYNTHETIC dataset) were trained on the LAION dataset [31]. However, a score of 40% on a 4-way multiple-choice task is still far below an acceptable level, demonstrating that even these models exhibit a serious lack of negation understanding.

Scaling CLIP does not address the negation problem. As shown in Figure 4b, scaling up the model size from ViT-B/32 (86M parameters) to ViT-L/14 (307M parameters) and ViT-H/14 (632M parameters) does not qualitatively improve negation understanding. While ViT-H/14 performs slightly better on COCO and VOC2007, it underperforms on SD-HNeg and MSR-VTT compared to ViT-B/32. These results suggest that increasing model size alone is not an effective strategy for addressing the fundamental issues with negation understanding.

Critical failures in high-stakes medical tasks. Figure 4c presents the results for the CheXpert MCQ-Neg task, where

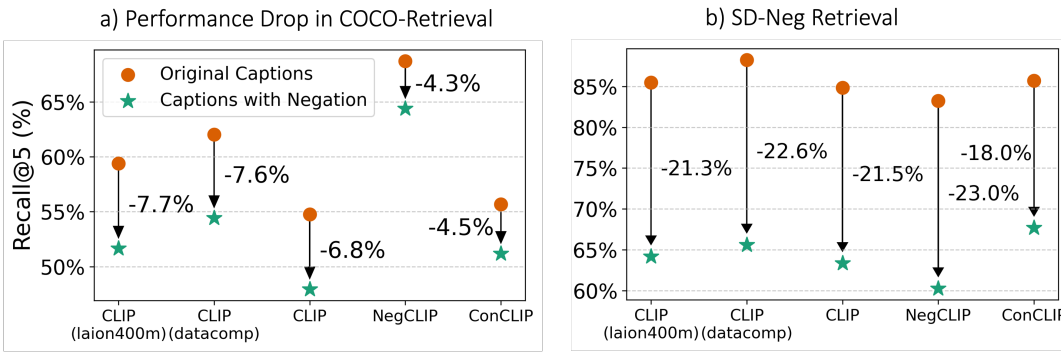

Figure 3. **Performance drop in recall@5 on (a) COCO and (b) SD-Neg text-to-image retrieval with negated captions (green stars) compared to original captions (orange circles).** All models show substantial drops in performance, with NegCLIP experiencing the largest drop of 23.0% on SD-Neg, which features hard negatives requiring stronger negation reasoning.

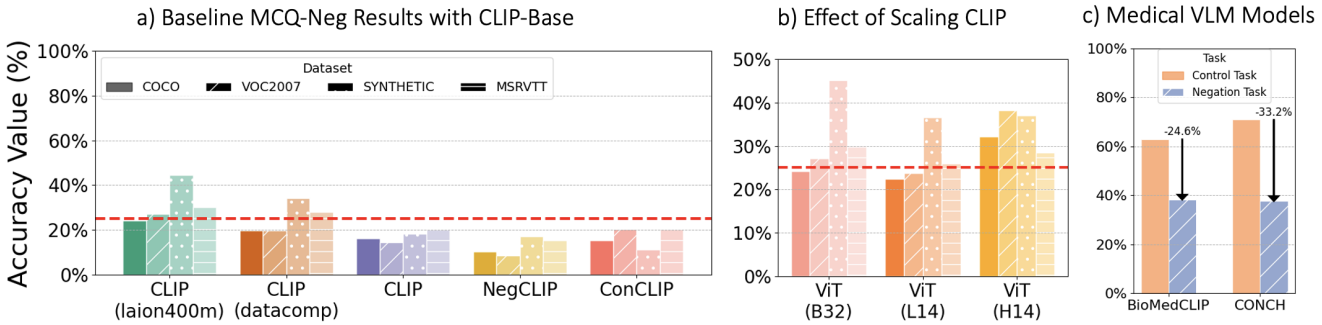

Figure 4. **MCQ-Neg performance breakdown for (a) baseline CLIP models, (b) the effect of scaling CLIP, and (c) performance drop of medical VLMs.** In (a), CLIP-based models perform worse than random guessing (shown as a red dashed line) on most datasets. In (b), scaling up CLIP models does not significantly improve negation understanding. In (c), medical VLMs models demonstrate a significant drop in performance on negation MCQs.

BioMedCLIP and CONCH exhibit substantial performance drops of 24.6% and 33.2%, respectively, when negation is introduced. This result is especially concerning in the context of medical diagnostics, where accurate interpretation of negation (e.g., the presence or absence of a condition such as Lung Opacity) is essential for correct diagnoses and favorable patient outcomes.

4.1. Why Do VLMs *Not* Understand Negation?

The results from NegBench reveal that CLIP VLMs struggle with different forms of negation understanding, motivating a deeper analysis into the underlying causes of these failures. In this section, we examine model performance across different MCQ types and analyze the embedding spaces of various models to uncover specific shortcut strategies that limit their negation comprehension.

Model performance varies widely across MCQ types. To understand why models perform below random chance, we categorize the MCQs into three types based on the correct answer template: Affirmation, Negation, and Hybrid. Figure 5 compares model accuracy across these MCQ types, with evaluations conducted in two settings: one using LLaMA 3.1 to paraphrase answer choices into natural-sounding sentences, and another using rigid linguistic templates. All models perform poorly on Negation MCQs, reflecting a general struggle with negation understanding.

Most models tend to select Negation sentences regardless of whether answers are templated or LLM-paraphrased, as seen in the selection frequencies shown to the right of the figure. This behavior likely arises from task design, where 67% of MCQs (Negation and Hybrid) lack a correct affirmative option, leading models to default to "This image does not include {pos}." These results suggest that models trained with CLIP-like objectives often adopt shortcut strategies that ignore specific words like "no."

The template-based results reveal more biases in model behavior. For instance, ConCLIP outperforms on Hybrid MCQs, achieving the highest accuracy, but fails entirely on Affirmation MCQs, scoring 0% on both image datasets. This bias is particularly prominent in the rigid template structure, where ConCLIP is skewed towards constructs like

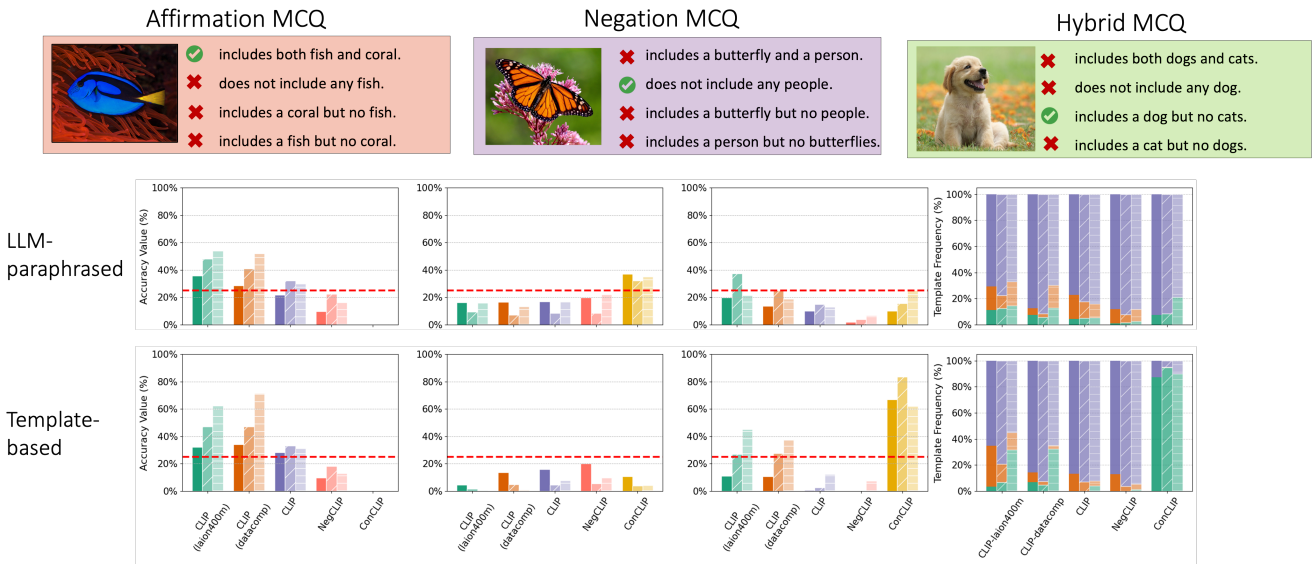

Figure 5. **Performance breakdown by MCQ type (Affirmation, Negation, Hybrid) across LLM-paraphrased (b) and template-based (c) answer choices.** Models show significant biases towards specific templates. Template selection frequency (right) reveals that models frequently default to Negation answers, especially when a positive object is incorrectly negated.**[TODO: Align+Legend]**

"This image includes X but not Y." In fact, as we will show next, ConCLIP maps all templated Hybrid captions to the same location in its embedding space.

Embedding analysis reveals VLM shortcut strategies. To investigate potential shortcut strategies, we analyze the embedding spaces of various models using 24 Affirmative ("X") and 24 Negated ("Not X") templates to create 48 captions per object. We apply PCA to the resulting embeddings (Figure 6). The templates are included in the appendix.

We observe varying behaviors across models. The overlapping embeddings for affirmative and negated captions in *CLIP* and *NegCLIP* suggest that these models do not distinguish between positive and negative statements, possibly due to a "bag-of-words" shortcut strategy [9, 42] that overlooks negation words. This explains why both models incorrectly select the Negation template, which negates positive objects, in Figure 5. *CoNCLIP* separates positive and negative captions but fails to distinguish between negative captions of different objects, collapsing all negative caption embeddings toward a single point (red circle).

We include the embeddings of a text-only Sentence Transformer [28] as a reference that effectively differentiates affirmative and negated captions along distinct "object type" and "negation" axes, exemplifying ideal separation.

Hybrid captions reveal more evidence of collapsed embeddings. Figure 7 extends the previous analysis to hybrid captions that combine affirmations and negations. It provides further evidence that *ConCLIP* employs a shortcut strategy for embedding linguistic negation, with hybrid and negated captions collapsing towards a single point (green circle), indicating significant compression along the negation axis. While *CLIP* and *NegCLIP* struggle to distinguish affirmative from negative statements, *NegCLIP* shows better separation for hybrid captions, which appear collapsed in the CLIP embedding space. This suggests that NegCLIP's poor performance on Hybrid MCQs might be due to a misalignment between the text and image encoders, rather than an inability to understand hybrid sentence structure. In contrast, the *Sentence Transformer* effectively distinguishes between different caption types and provides semantically guided representations. For example, it aligns "flowers but not cats" along the line connecting "cats" and "not flowers."

5. A Data-Centric Approach for Improving Negation Understanding

Our analysis in Section 4.1 suggests that the poor negation understanding of CLIP-based models is caused by overreliance on linguistic shortcut strategies. We hypothesize that these shortcuts arise from data limitations during training. In CLIP, training data lacks examples with explicit negation, leaving it unable to distinguish negated and affirmed concepts. In contrast, ConCLIP's training data overfits to a single hybrid linguistic template, limiting its ability to generalize across varied negation structures. In this section, we explore data-centric strategies to address these gaps, introducing a dataset that not only includes diverse negation examples but also spans a range of linguistic styles, aiming to

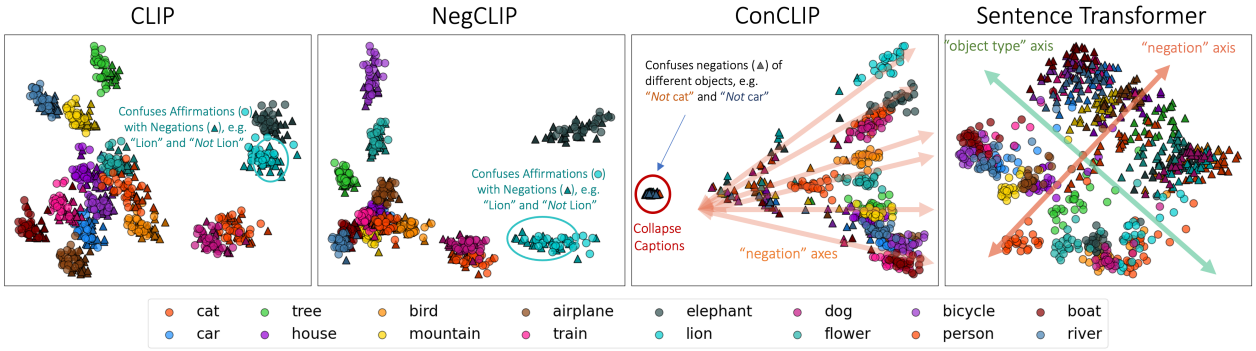

Figure 6. **PCA projections of Affirmative (dots) and Negative (triangles) Caption Embeddings for Multiple Objects.** The Sentence Transformer shows clear separation along 'object type' and 'negation' axes, while CoNCLIP demonstrates compression along negation axes (treating all negated captions as identical). CLIP and NegCLIP lack separation between affirmative and negated captions.

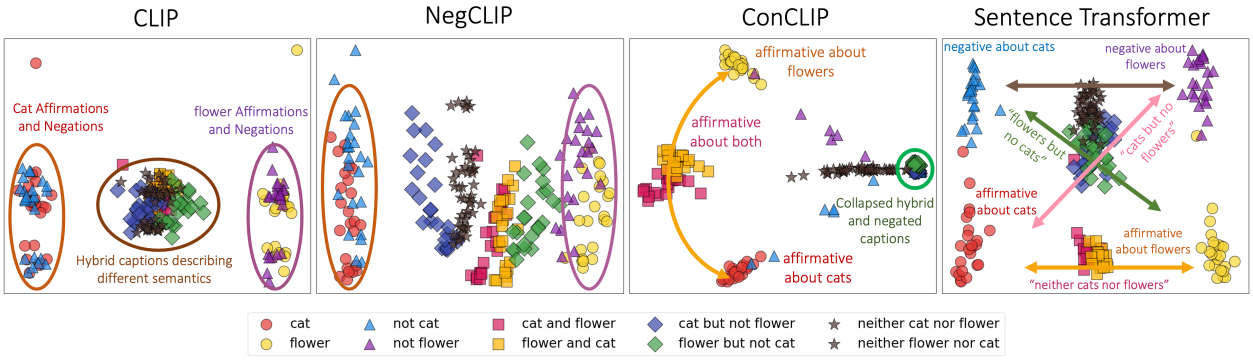

Figure 7. **PCA of Affirmative (dots and squares), Negated (triangles and stars), Hybrid captions (diamonds).** ConCLIP compresses negated and hybrid captions (green circle), while CLIP and NegCLIP fail to separate affirmative and negated captions (red and purple ovals). Sentence Transformer exhibits clear separability and semantic representation, exemplifying the desired behavior.

aiming to create embedding spaces that effectively separate affirmative and negated concepts.

5.1. Synthetic Negation Dataset Creation

We augment the CC12M dataset [4], which contains approximately 10 million image-text pairs, to generate two synthetic datasets with negated captions: Syn-Neg-Cap and Syn-Neg-MCQ. Our goal is to expose models to a wide variety of negation scenarios and improve their ability to encode negated statements. The process follows these steps:

1. **Object Extraction**: Using LLaMA 3.1 [6], we extract positive objects (those mentioned in the caption) and negative objects (contextually relevant but not present) from each image-caption pair in CC12M.
2. **Visual Verification**: An open-vocabulary object detector [22] verifies the presence of positive objects and ensures the absence of the negative objects in the image. This step is crucial to avoid introducing incorrect negations that could confuse the model.
3. **Caption Generation**: For each image, we generate multiple new captions that incorporate negated objects into the original captions. LLaMA 3.1 is used to ensure the generated captions are natural-sounding and reflect realistic negation scenarios found in retrieval queries. This process is flexible and agnostic to the exact number of captions generated per image.

We construct two variants of the synthetic dataset:

- **Syn-Neg-Cap**: For each image in CC12M, we generate three captions incorporating negated objects, resulting in approximately 30 million synthetic captions.
- **Syn-Neg-MCQ**: For this variant, we generate four captions per image, one of which is correct and the other three are hard negatives, selected based on object annotations. This format provides stronger training signals for fine-grained negation understanding. Syn-Neg-MCQ consists of around 40 million synthetic captions.

We will release the extracted object annotations for each image in CC12M, along with the corresponding URLs, and all the generated captions in Syn-Neg-Cap and Syn-Neg-MCQ. This will help the community build on our dataset and advance negation understanding and multimodal retrieval research.

5.2. Fine-Tuning with Negation-Enriched Data

Standard CLIP Objective on Syn-Neg-Cap. Let $\mathcal{B}_{\text{cap}} = \{(I_i, T_i)\}_{i=1}^{N}$ represent a batch of N image-caption pairs from Syn-Neg-Cap, where each image I_i is paired with a caption T_i that describes present and absent objects in the image. For each batch $\mathcal{B}_{\text{cap}}$, we compute a similarity matrix $S \in \mathbb{R}^{N \times N}$, where each element $S_{j,k}$ represents the cosine similarity between the j-th image and the k-th caption. The CLIP objective applies a symmetric cross-entropy loss over this matrix, encouraging high similarity for correct image-caption pairs and low similarity for incorrect pairs. This loss is denoted as $\mathcal{L}_{\text{CLIP}}(\mathcal{B}_{\text{cap}})$ and provides the model with diverse negation examples in a contrastive learning setup.

Multiple-Choice Objective on Syn-Neg-MCQ. Let $\mathcal{B}_{\text{mcq}} = \{(I_i, T_{i,1}, T_{i,2}, T_{i,3}, T_{i,4})\}_{i=1}^{M}$ represent a batch of M examples from Syn-Neg-MCQ, where each image I_i has four associated captions $\{T_{i,j}\}_{j=1}^{4}$, with one caption correctly describing the image and the others serving as hard negatives. To fine-tune on Syn-Neg-MCQ, we compute the cosine similarity between each image and its four caption options to obtain a set of logits for each image-option pair.

The multiple-choice loss $\mathcal{L}_{\text{MCQ}}(\mathcal{B}_{\text{mcq}})$ is then computed by applying a cross-entropy loss over the logits, with the correct answer index as the target. This loss encourages the model to assign higher similarity to the correct caption and lower similarity to the hard negative captions:

$$\mathcal{L}_{\text{MCQ}}(\mathcal{B}_{\text{mcq}}) = -\frac{1}{M}\sum_{i=1}^{M}\log\frac{\exp(\text{logits}_{i,\text{correct\_answers}_i})}{\sum_{j=1}^{4}\exp(\text{logits}_{i,j})}, \tag{1}$$

where correct_answers_i indicates the index of the correct caption for the i-th image.

Combined Training Objective. The final objective combines the contrastive loss on Syn-Neg-Cap with the MCQ loss on Syn-Neg-MCQ, weighted by α and β to balance their contributions. The total loss for one batch is:

$$\mathcal{L}_{\text{Total}} = \alpha\mathcal{L}_{\text{CLIP}}(\mathcal{B}_{\text{cap}}) + \beta\mathcal{L}_{\text{MCQ}}(\mathcal{B}_{\text{mcq}}). \tag{2}$$

Evaluation Protocol. To assess the impact of our data-centric approach, we fine-tune two pretrained models (OpenAI CLIP and NegCLIP) on Syn-Neg-Cap using the contrastive loss $\mathcal{L}_{\text{CLIP}}$. Additionally, we fine-tune both models on the combined Syn-Neg-Cap and Syn-Neg-MCQ datasets using $\mathcal{L}_{\text{Total}}$ in Equation (2). For comparison, we fine-tune these models on the original CC12M dataset to isolate the effect of our negation-enriched datasets. Our goal is to demonstrate that CLIP models can significantly improve their understanding of negation with the right data.

Model	Fine-tune data	R@5 (↑)	R-Neg@5 (↑)	MCQ (↑)
CLIP	None	54.8	48.0	16.3
	CC12M	58.8	54.5	11.2 (↓5.1)
	Syn-Neg-Cap	**58.5**	**57.8**	**14.7** (↓1.6)
	Syn-Neg-Full	**54.2**	**51.9**	**46.9** (↑30.6)
NegCLIP	None	68.7	64.4	10.2
	CC12M	70.2	66.0	10.6 (↑0.4)
	Syn-Neg-Cap	**68.6**	**67.5**	**12.5** (↑2.3)
	Syn-Neg-Full	**69.0**	**67.0**	**51.0** (↑40.8)

(a) COCO Evaluation

Model	Fine-tune data	R@5 (↑)	R-Neg@5 (↑)	MCQ (↑)
CLIP	None	50.6	45.8	20.1
	CC12M	53.7	49.9	16.9 (↓3.2)
	Syn-Neg-Cap	**54.1**	**53.5**	**20.1** (0.0)
	Syn-Neg-Full	**46.9**	**43.9**	**35.6** (↑15.5)
NegCLIP	None	53.7	51.0	15.3
	CC12M	56.4	52.6	16.8 (↑1.5)
	Syn-Neg-Cap	**56.5**	**54.6**	**18.9** (↑3.6)
	Syn-Neg-Full	**54**	**51.5**	**36.6** (↑21.3)

(b) MSR-VTT Evaluation

Table 1. **Comparison of fine-tuning datasets** on performance metrics across COCO and MSR-VTT, fine-tuned on respective datasets and evaluated on retrieval and multiple-choice questions. Differences in MCQ accuracy from the baseline are shown, with increases of +1 or more highlighted.

We evaluate the models on two tasks: (i) text-to-image and text-to-video retrieval on COCO and MSR-VTT, both with and without negated queries, and (ii) image-to-text and video-to-text MCQ tasks, where models select the correct caption from four options. The results are shown in Table 1.

Results. Fine-tuning CLIP on Syn-Neg-Cap leads to significant improvements in handling negated queries in retrieval tasks. On COCO, the R-Neg@5 score increases by 10.6%, while the gap between R@5 and R-Neg@5 (ΔR) narrows from 6.8% to 0.5%, indicating that the model now performs nearly as well on negated queries as on standard ones. A similar pattern is observed on MSR-VTT.

However, fine-tuning on Syn-Neg-Cap alone does not improve performance on the MCQ task, suggesting that the contrastive objective is insufficient for learning fine-grained negation comprehension. To address this, we fine-tune CLIP and NegCLIP on the combined Syn-Neg-Cap and Syn-Neg-MCQ datasets, yielding substantial improvements on MCQ tasks. On COCO-MCQ, for instance, CLIP's accuracy rises from 16.3% to 56.9%, a 40.6% increase.

Overall, fine-tuning on our synthetic datasets significantly enhances the models' negation understanding without sacrificing performance on standard retrieval tasks. This demonstrates that CLIP-based models can be made more robust to negated queries with the right data, reducing their reliance on shortcut strategies.

Ablation: Effect of varying α. The table below shows the impact of varying the weight factor α in the combined

loss $\mathcal{L}_{\text{Total}} = \alpha\mathcal{L}_{\text{CLIP}} + (1-\alpha)\mathcal{L}_{\text{MCQ}}$ when fine-tuning CLIP on Syn-Neg-Full. As β increases, more weight is placed on the original CLIP contrastive objective, while a lower β emphasizes the MCQ loss.

α	0	0.5	0.9	0.99	1
COCO Recall@5 (%)	33.9	37.3	47.6	54.2	58.5
COCO MCQ Acc (%)	61.0	54.7	50.5	46.9	14.7

Properly tuning α is important to strike a balance, adapting to fine-grained MCQs while maintaining standard retrieval performance.

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