Training-free Zero-shot
Composed Image Retrieval via
***Wei**ghted **Mo**dality Fusion and Similarity*

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What is Composed Image Retrieval (CIR)?

Definition

- Reference Image: Base visual input.
  - (eg. A blue T-Shirt)

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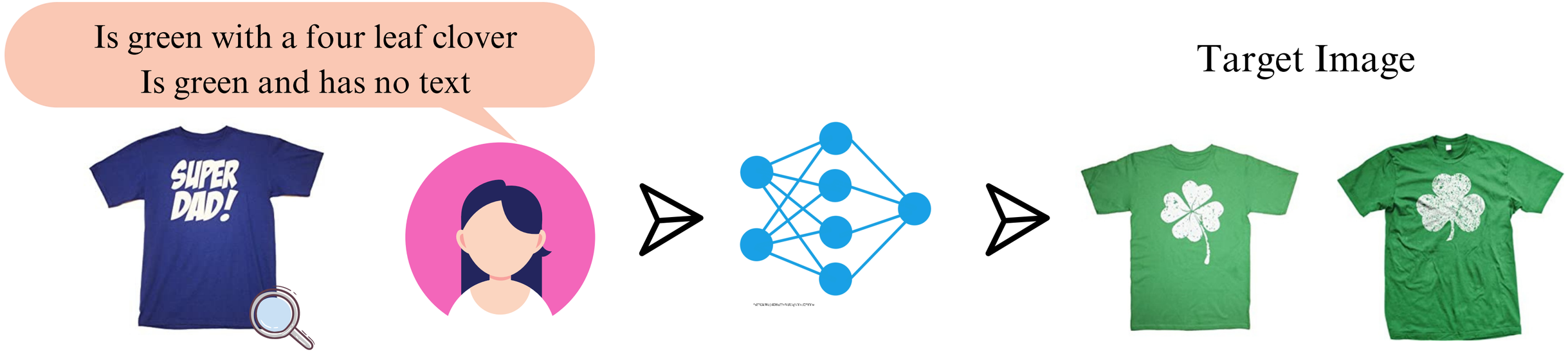


Applications of CIR: What can we achieve?

Applications

- Fashion recommendation
  - (e.g., "The user might also like a 4-leaf clover design one").

The user also likes the 4-leaf clover

Recommend this item

Applications of CIR: What can we achieve?

Applications

- Fashion recommendation
  - (e.g., "The user might also like a 4-leaf clover design one").
- Real-world tasks - Image database search engine
  - (e.g., "Find a similar photo but without the people in the picture").

The user also likes the 4-leaf clover

Recommend this item

I want a image without the people

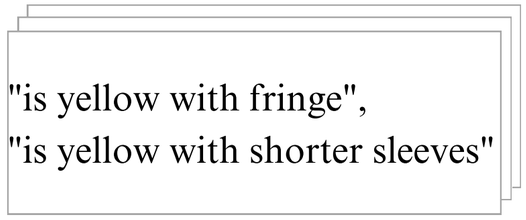
Database find and return relative image

Challenges in CIR

- Requires labor-intensive triplet collection for supervised learning.

Issue: Triplet collection

1. Query Image



2. Modified Descriptions

3. Target Image

Challenges in CIR

- Requires labor-intensive triplet collection for supervised learning.
- Models trained on specific domain often fail to generalize well to different domains.

Issue: Triplet collection

1. Query Image

"is yellow with fringe",
"is yellow with shorter sleeves"

2. Modified Descriptions

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Issue: Dataset is for specific domain

≠

Challenges in CIR

- Requires labor-intensive triplet collection for supervised learning.
- Models trained on specific domains often fail to generalize well to different domains.
- Previous Zero-shot CIR relies heavily on additional datasets pertaining to fusion.

Issue: Triplet collection

1. Query Image

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Issue: Dataset is for specific domain

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Scalability vs. Efficiency

- State-of-the-art (SOTA) methods excel at large scales but are resource-intensive.

Model Name	CLIP B/32	CLIP L/14	CLIP H/14	CLIP G/14
Number Of Parameter	151M	428M	986M	1.37B

Scalability vs. Efficiency

- State-of-the-art (SOTA) methods excel at large scales but are resource-intensive.
- Smaller-scale models are more efficient but often lack performance.

Model Name	CLIP B/32	CLIP L/14	CLIP H/14	CLIP G/14
Number Of Parameter	151M	428M	986M	1.37B

Developing Training-free Approaches for CIR

CIR Challenge

Scalability vs. Efficiency

Query Image

"is yellow with fringe",
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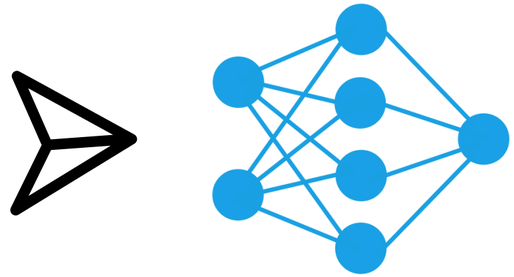
Modified Descriptions



Target Image

Developing Training-free Approaches for CIR

CIR Challenge

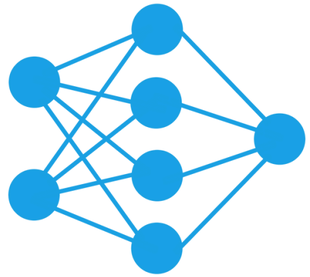
Scalability vs. Efficiency

- A training-free method that maintains
  a. Efficiency
  b. Ensures generalization
  c. Balances with scalability

Query Image

"is yellow with fringe",
"is yellow with shorter sleeves"

Modified Descriptions

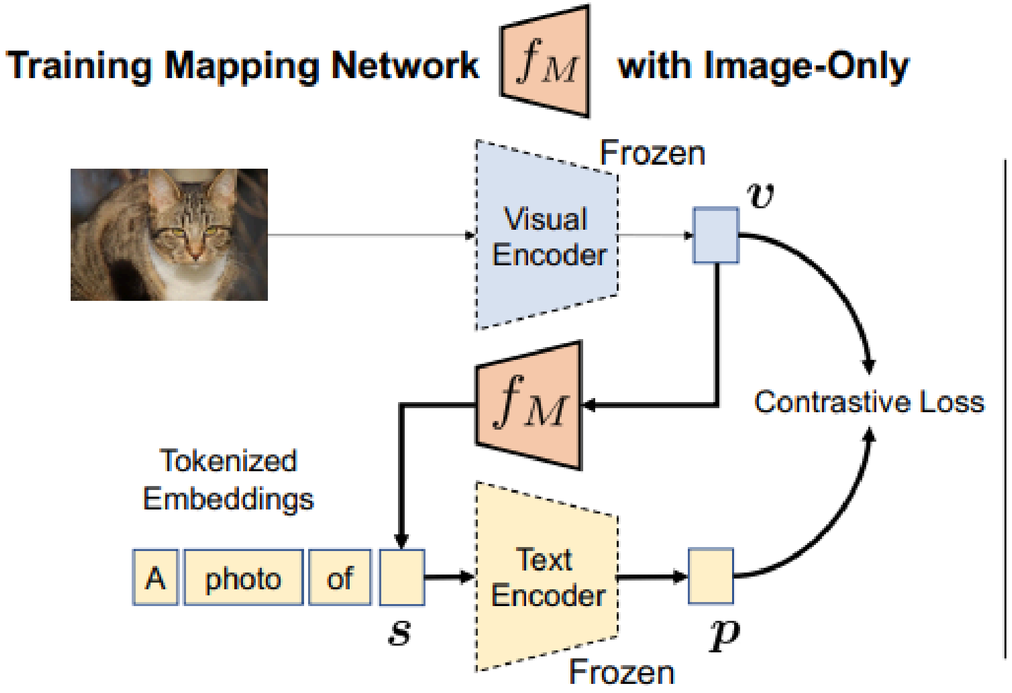


A method to solve this

Target Image

Pic2Word: Pioneering Zero-Shot CIR with Pseudo-Word Mappings

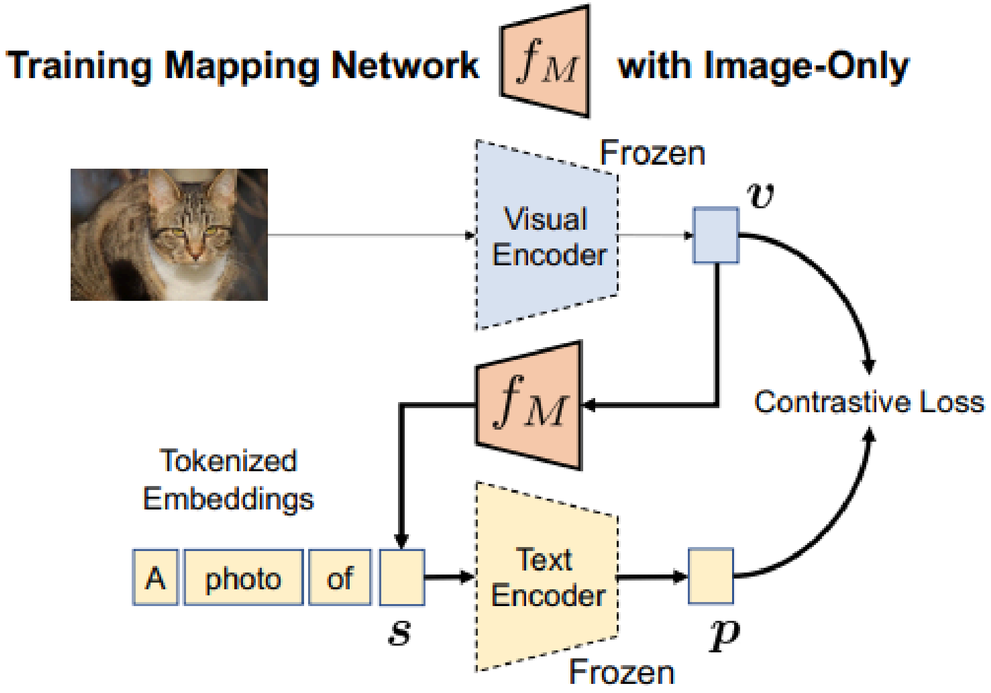
Mapping network to align image and text embeddings.

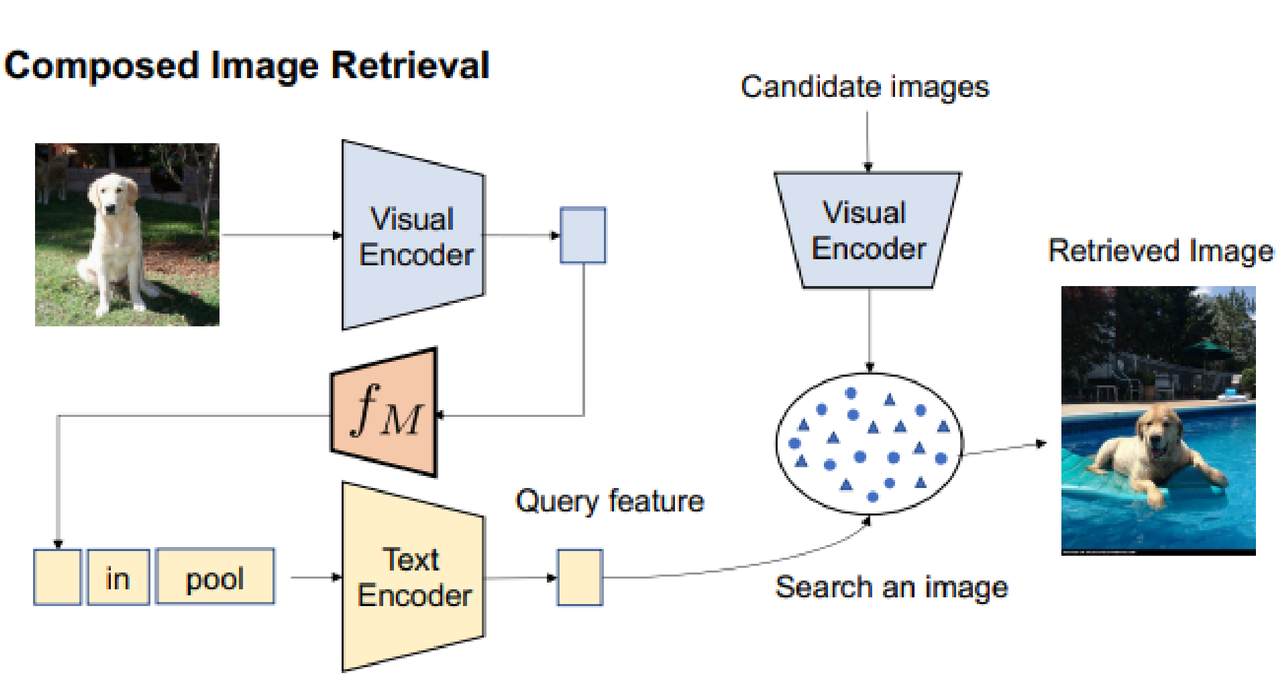


Pic2Word: Pioneering Zero-Shot CIR with Pseudo-Word Mappings

Mapping network to align image and text embeddings.

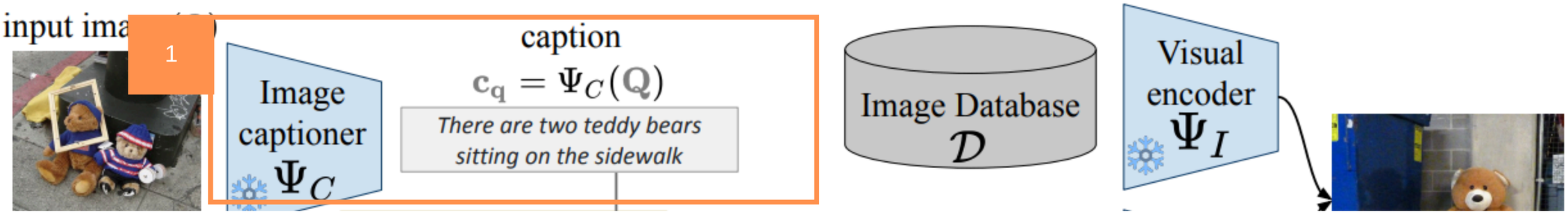
Pseudo-word tokens are used to complete text prompts for retrieval





CIReVL: Achieving Training-Free ZS-CIR via Vision-Language Embeddings

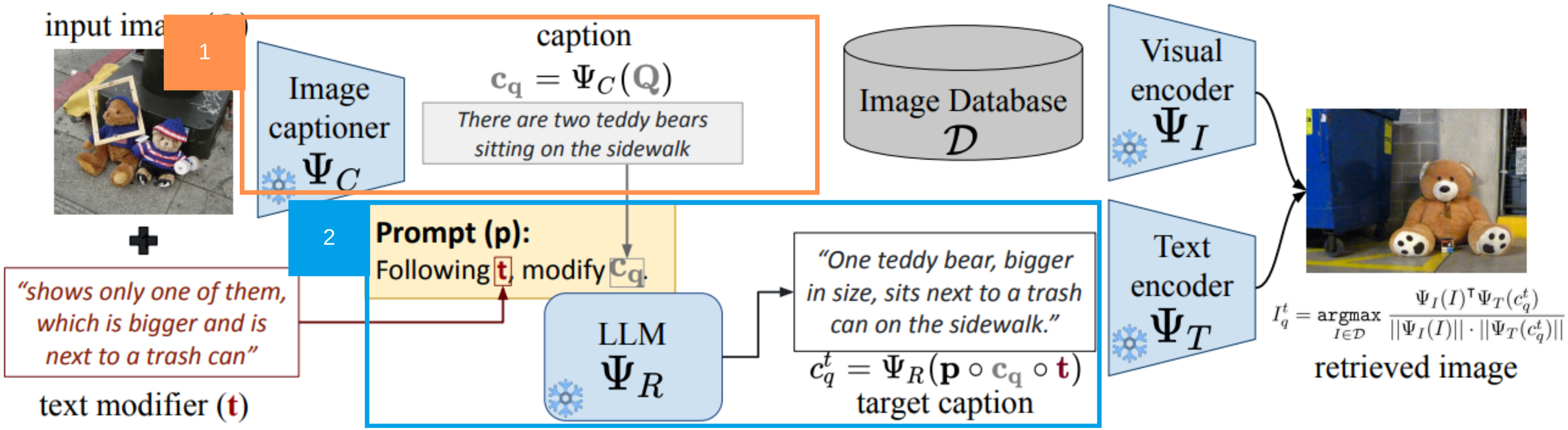
1 Captioning the image using a VLM



CIReVL: Achieving Training-Free ZS-CIR via Vision-Language Embeddings

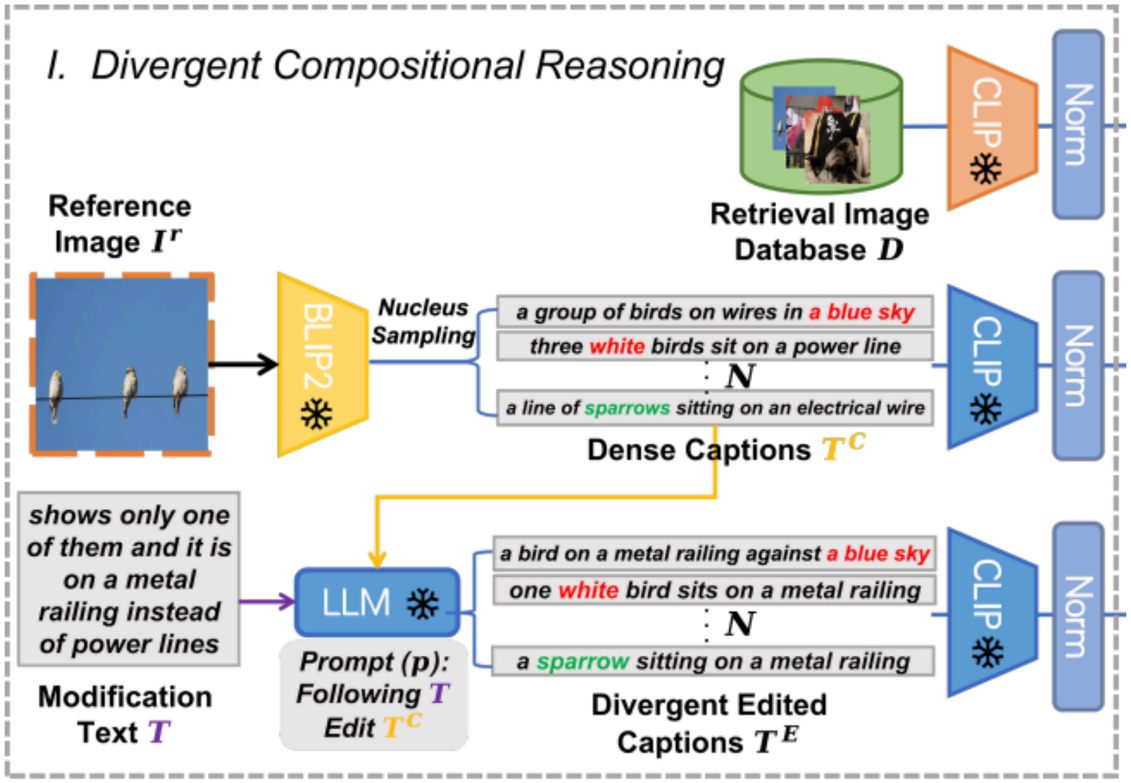
1 Captioning the image using a VLM

2 LLM creates the target image description



LDRE: Advancing ZS-CIR with Diverse Captions and LLM Reasoning

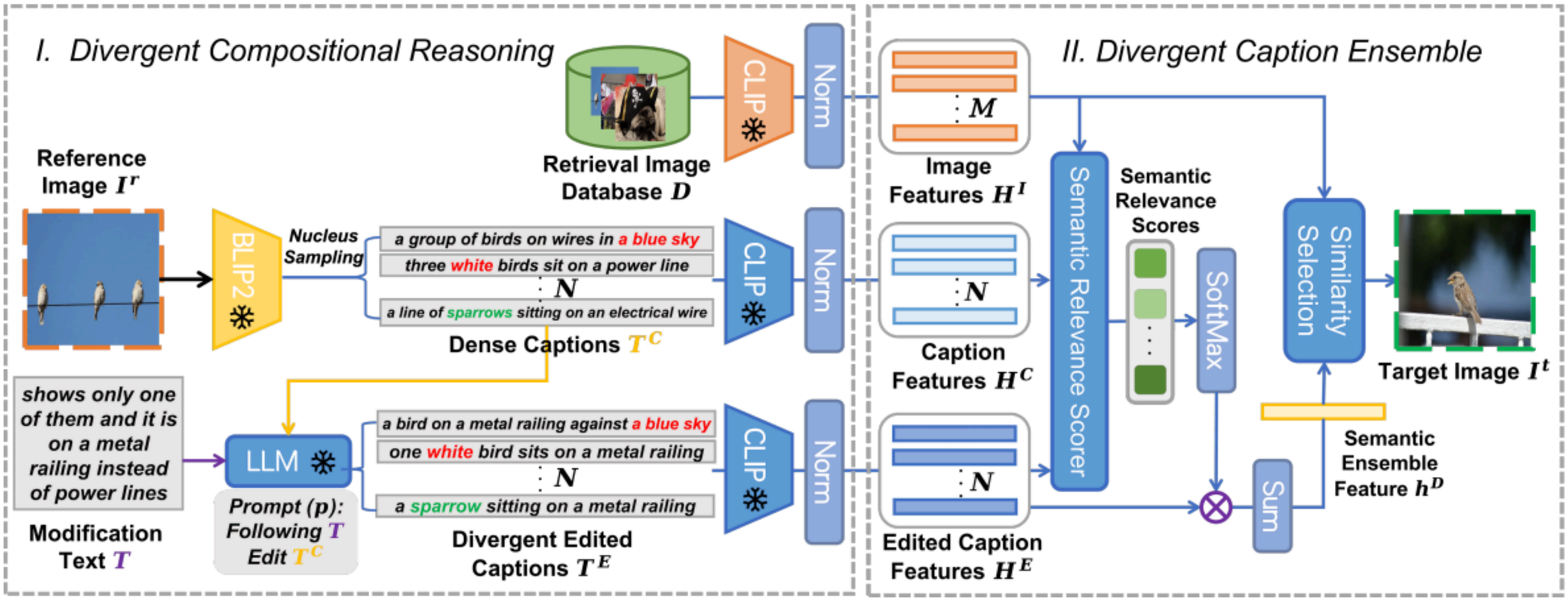
Diverse reasoning to
cover possible semantics.



LDRE: Advancing ZS-CIR with Diverse Captions and LLM Reasoning

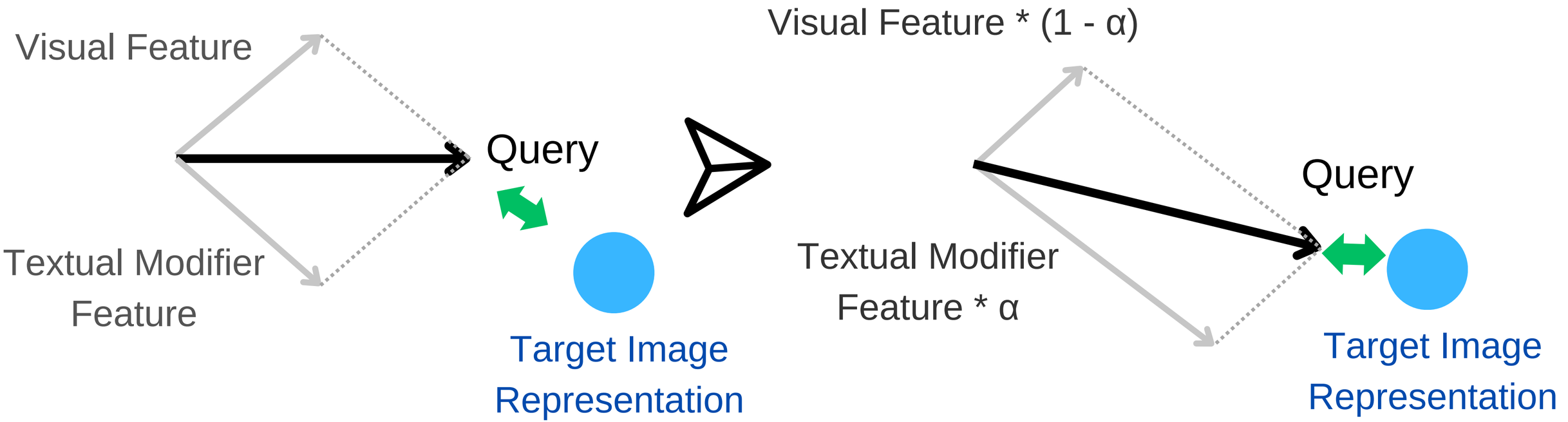
Diverse reasoning to cover possible semantics.

Ensemble integrates captions for robust retrieval.



Our idea to achieve training-free zero-shot CIR: WeiMoCIR

- Modality Fusion: Combines image and text features using weighted averages.
- Weighted Similarity: Balances query-to-image and query-to-caption relevance.



Our idea to achieve training-free zero-shot CIR: WeiMoCIR

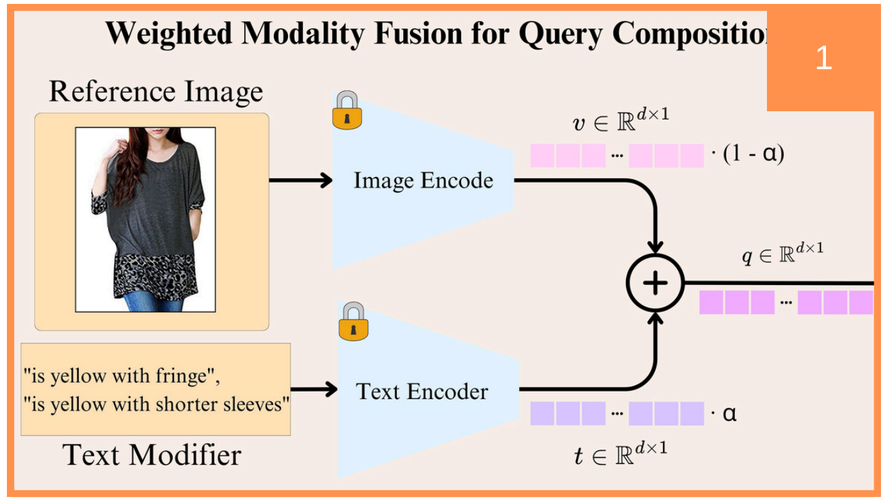
- Modality Fusion: Combines image and text features using weighted averages.
- Weighted Similarity: Balances query-to-image and query-to-caption relevance.
- Enhanced Representations via MLLMs: The idea stems from the fact that image descriptions inherently contain potential pseudo-queries.

Prompt

MLLM

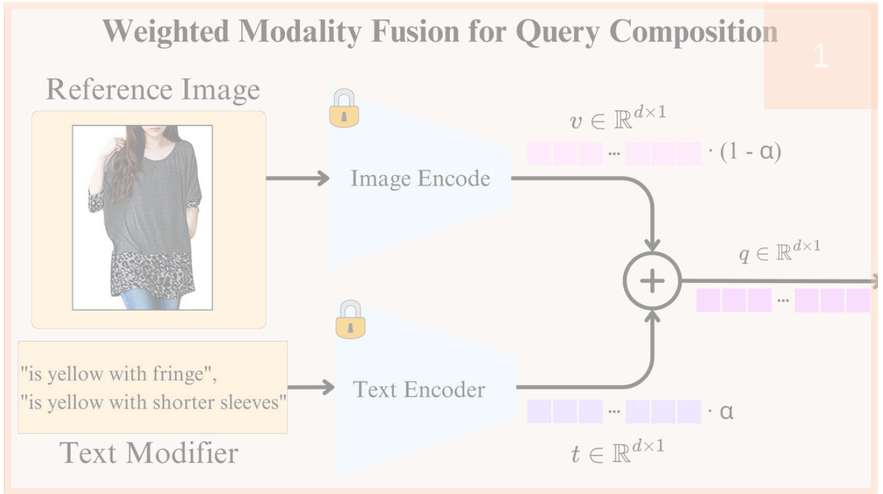
"Yellow short-sleeve t-shirt with fringe at the bottom.",
"V-neck t-shirt with yellow and gray color block design.",
"Yellow t-shirt with a raw hem and distressed detailing."

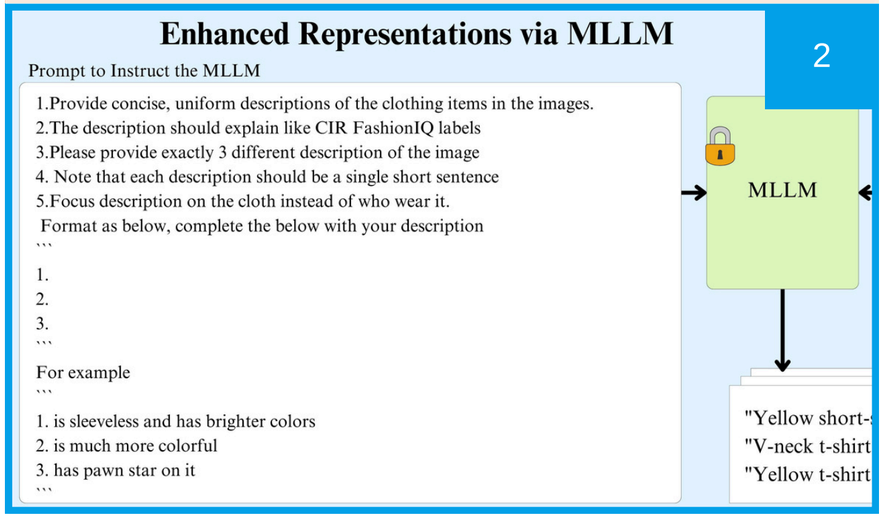
WeiMoCIR pipeline - OverView



1 Weighted Modality Fusion (Query Representation)

WeiMoCIR pipeline - OverView





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2 Enhanced Representations via MLLMs (Database Representation)

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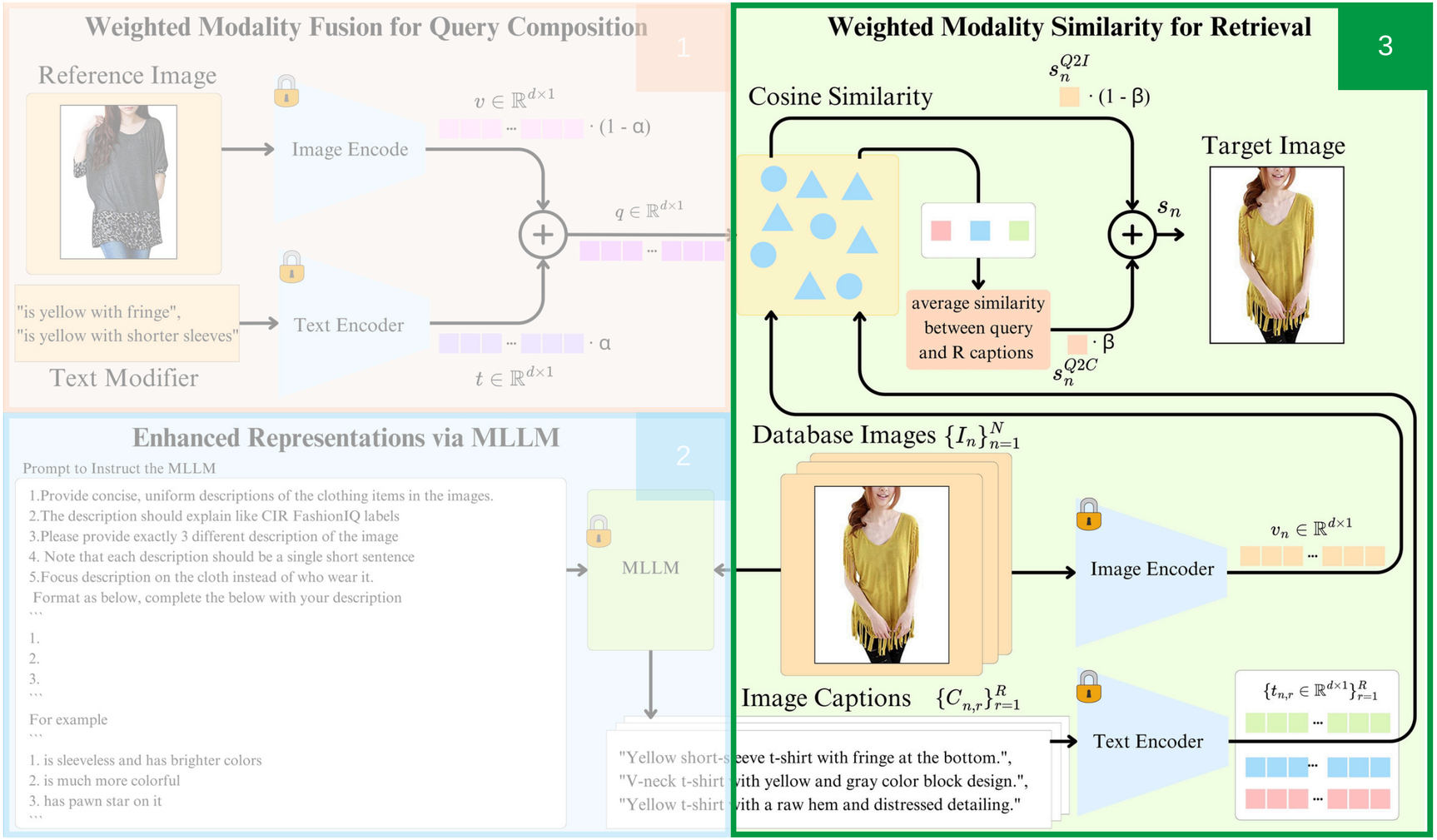
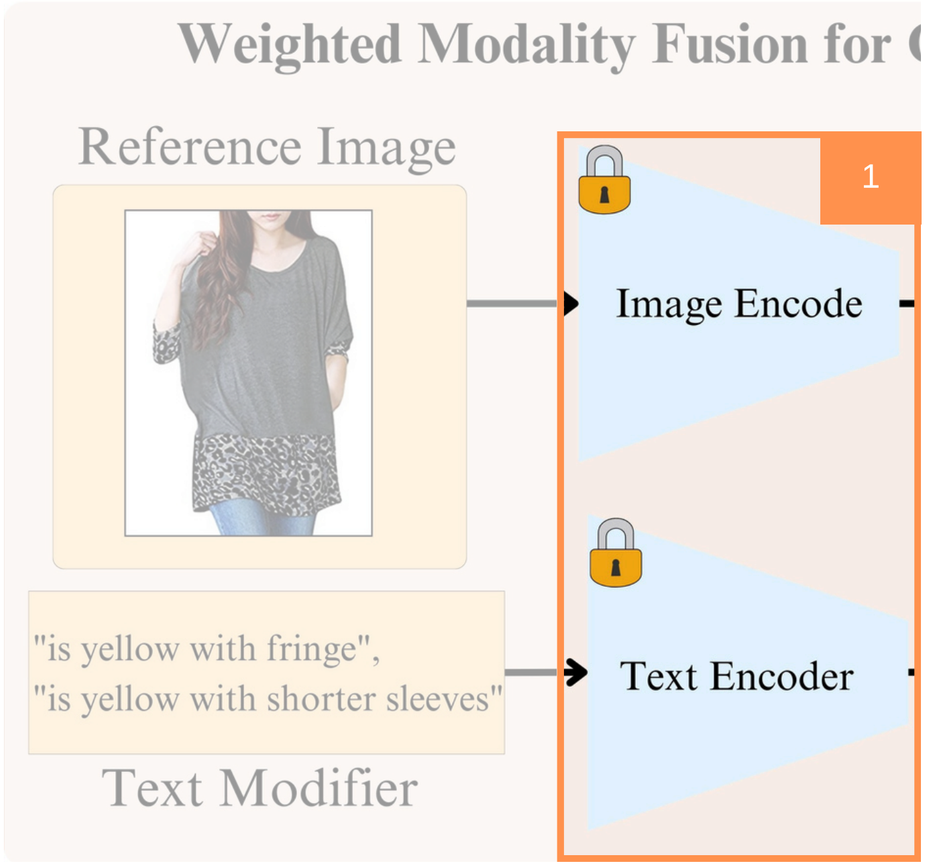


1 **Weighted Modality Fusion** (Query Representation)

2 **Enhanced Representations via MLLMs** (Database Representation)

3 **Weighted Modality Similarity for retrieval** (Similarity Computation)

Weighted Modality Fusion



1

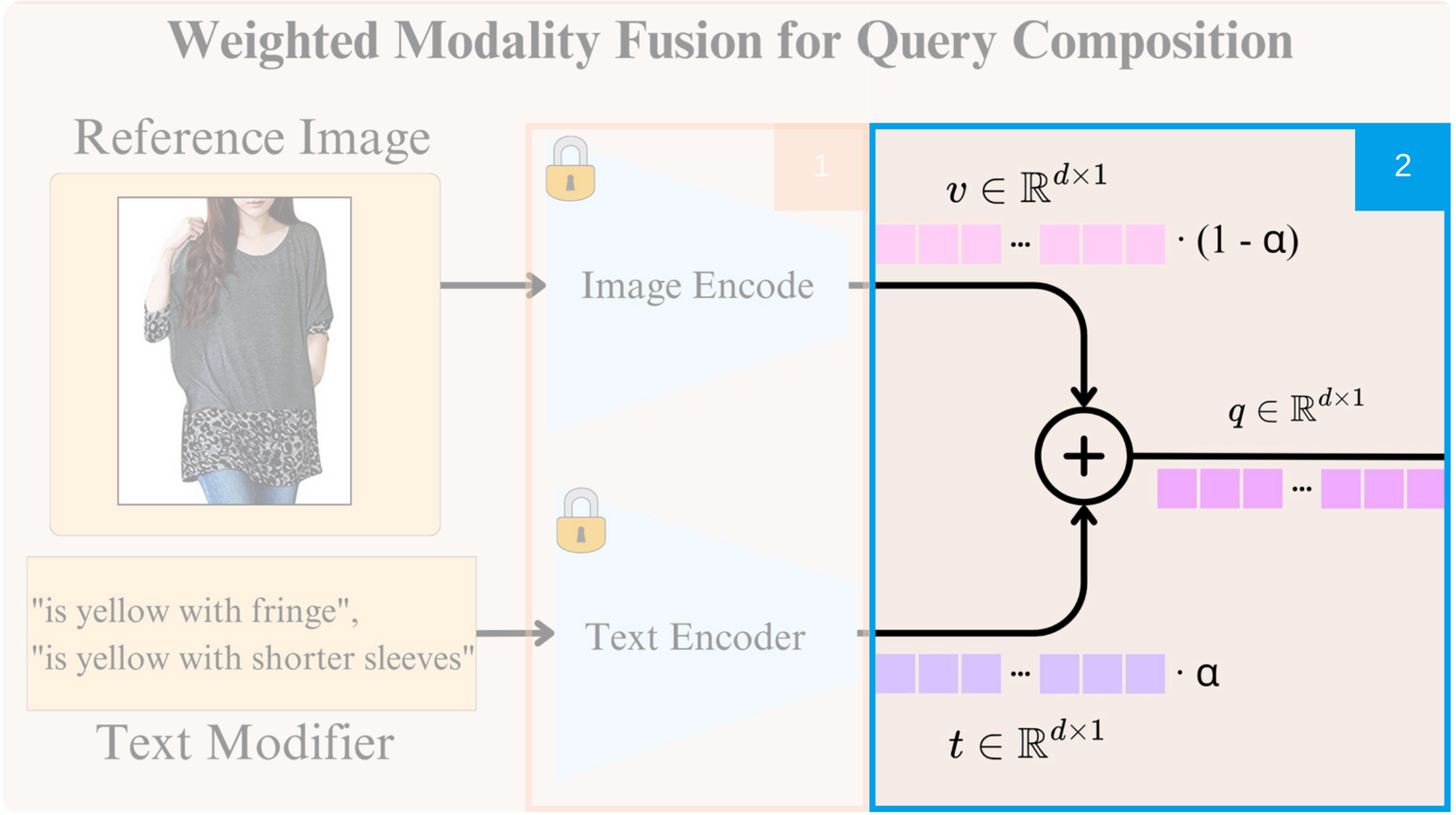
Replaceable VLM

Vision encoder and text encoder are used as feature extractors.

Visual Feature $v_n = f_\theta(I_n) \in \mathbb{R}^{d\times 1}$

Text Feature $t_{n,r} = f_\phi(C_{n,r}) \in \mathbb{R}^{d\times 1}$

Weighted Modality Fusion



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2

Combines image and text into a unified query

$$q = \mathcal{M}(v,t) = (1-\alpha)\cdot v + \alpha \cdot t$$

α: Balances contributions of visual and textual features.

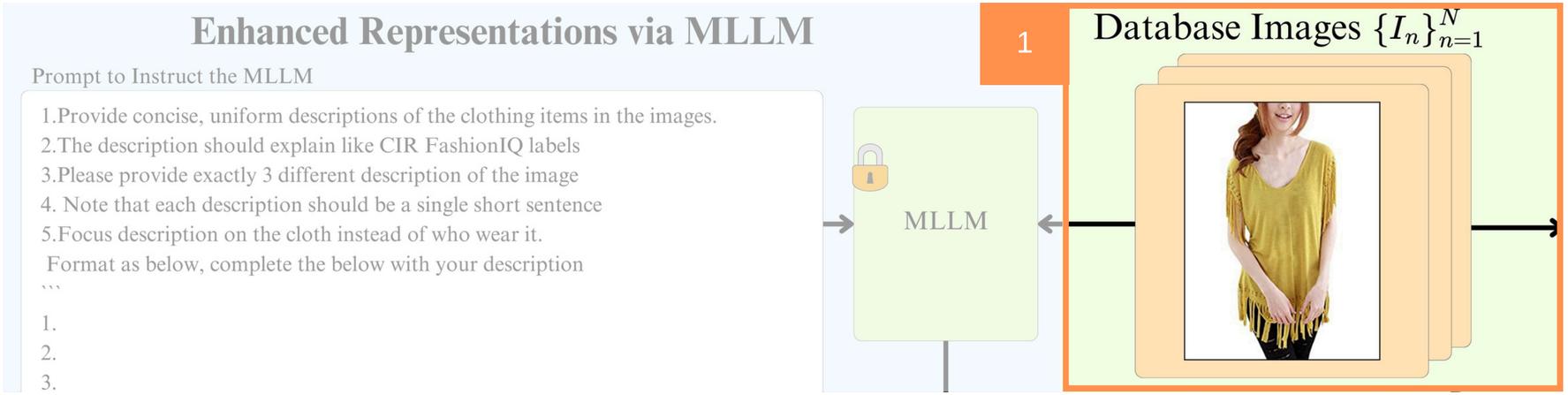
Enhanced Representations via MLLMs

- Generate captions for database images using MLLMs
- Captions provide semantic context for image features.

1

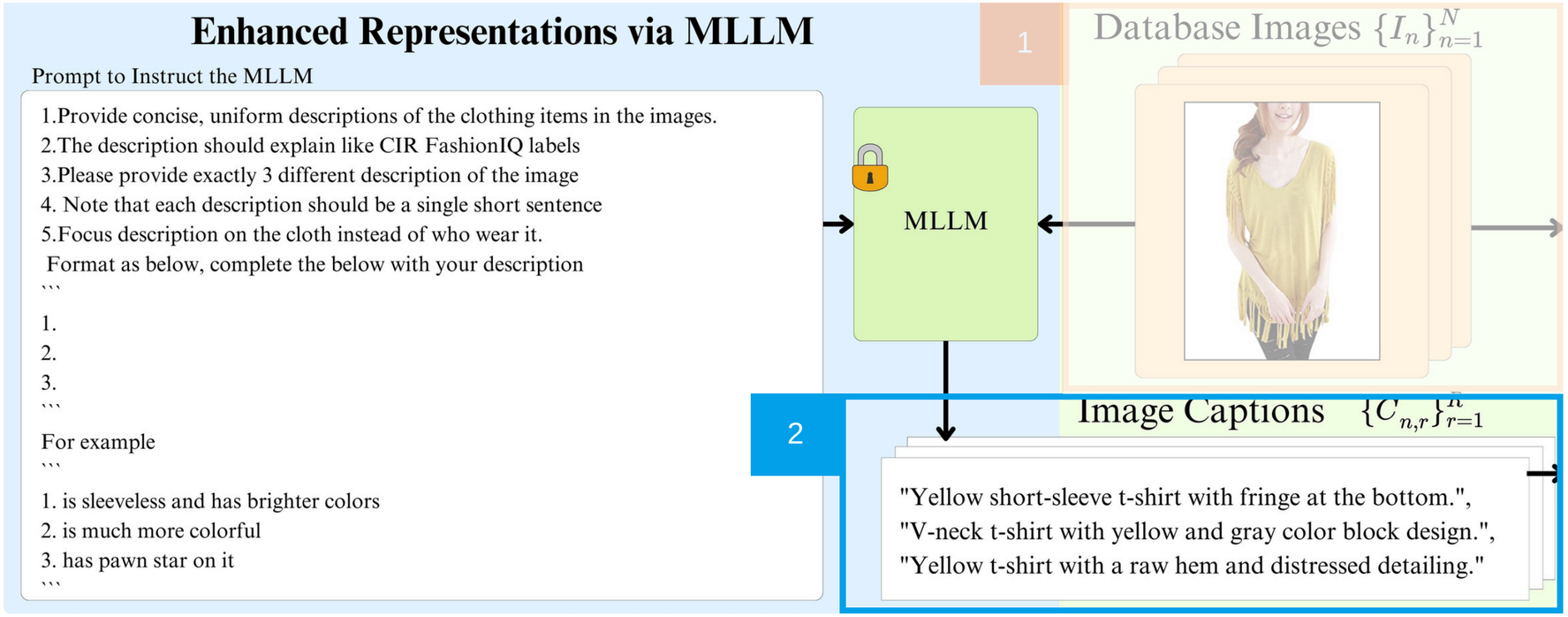
$$\{I_n\}_{n=1}^{N}$$

N pieces of
Database Images



Enhanced Representations via MLLMs

- Generate multiple captions for each database image using MLLMs (In this experience we set R = 3)
- Captions provide semantic context for image features.



1

$$\{I_n\}_{n=1}^{N}$$

N pieces of Database Images

MLLM

2

$$\{C_{n,r}\}_{r=1}^{R}$$

A set of R captions for N pieces of Database Images

Weighted Modality Similarity for retrieval

1

Feature Extraction

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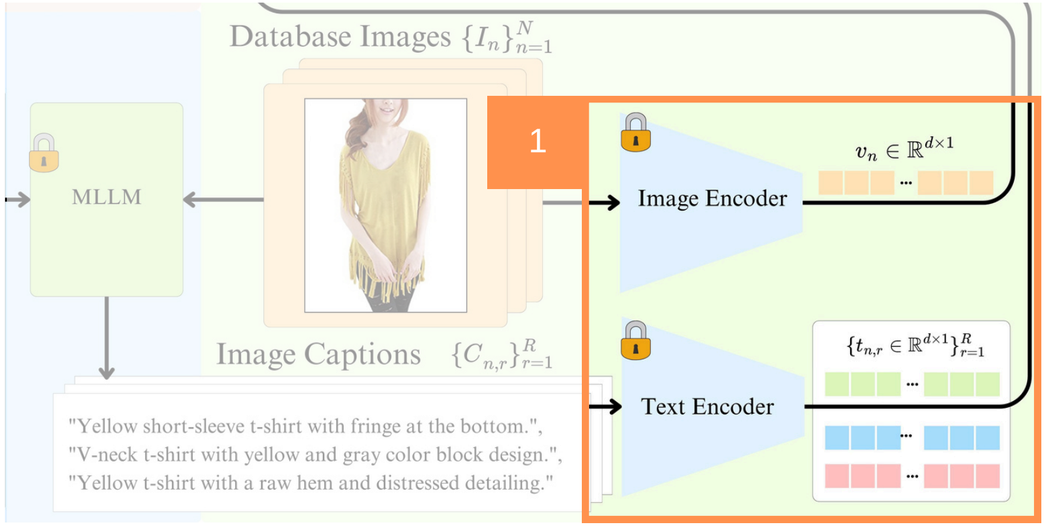
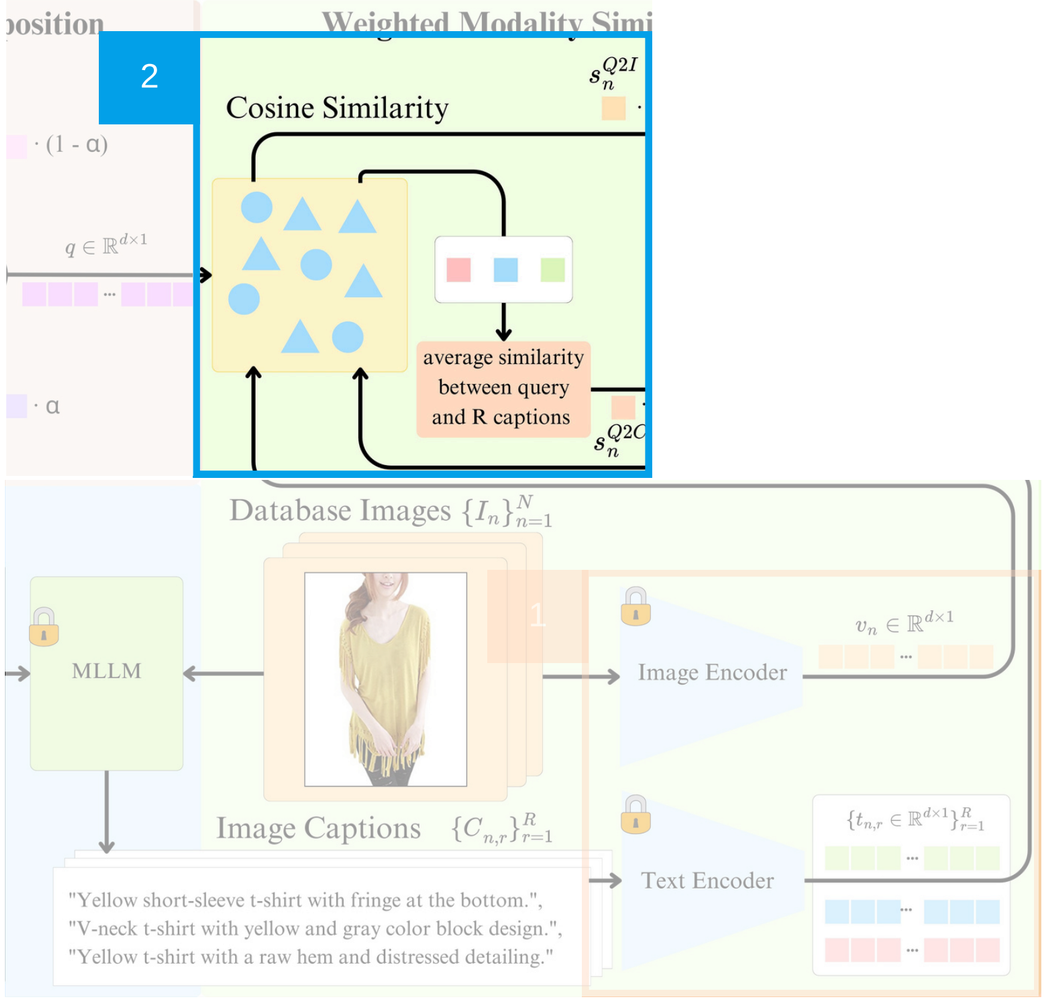


Weighted Modality Similarity for retrieval



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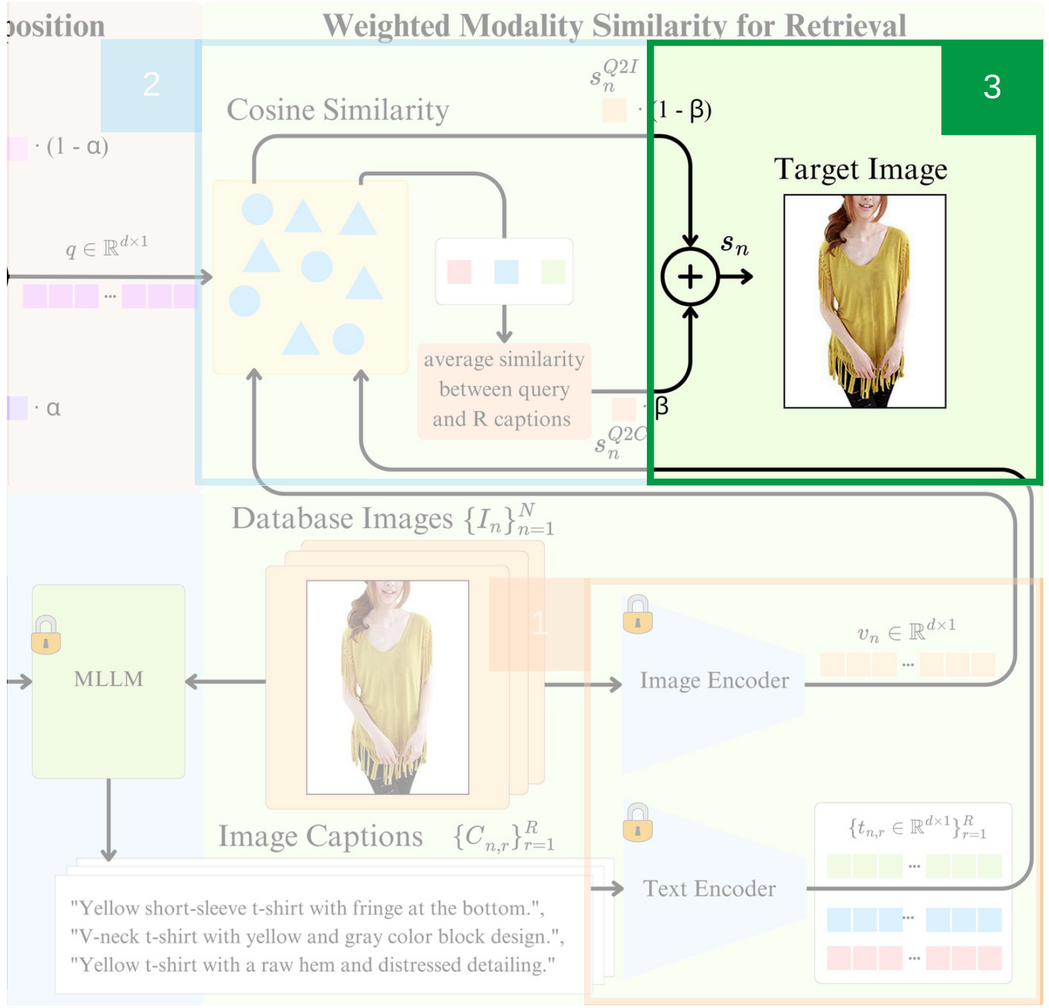
2

Combines

- Query-to-Image $s_n^{Q2I} = \text{sim}(q, v_n)$
- Query-to-Captions $s_n^{Q2C} = \frac{1}{R}\sum_{r=1}^{R}\text{sim}(q, t_{n,r})$

Weighted Modality Similarity for retrieval



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- Query-to-Captions $s_n^{Q2C} = \frac{1}{R}\sum_{r=1}^{R} \mathrm{sim}(q, t_{n,r})$

3

Weighted Similarity Score

$$s_n = (1-\beta)\cdot s_n^{Q2I} + \beta \cdot s_n^{Q2C}$$

Introduction to dataset

- FashionIQ: Focuses on fashion-related composed image retrieval.

Dataset	Domain
FashionIQ	Fashion images
CIRR	Real-world data

Introduction to dataset

- FashionIQ: Focuses on fashion-related composed image retrieval.
- CIRR (Composed Image Retrieval on Real-life images): Real-world, complex descriptors for composed retrieval.

Dataset	Domain
FashionIQ	Fashion images
CIRR	Real-world data

Evaluation Metrics and Baseline

Evaluation Metrics

- Recall@K: Measures how often the correct result is in the top-K retrieved items.

Dataset	Domain	Metric
FashionIQ	Fashion images	R@10, R@50
CIRR	Real-world data	R@1, R@5, R@10, R@50, Rsubset@1, Rsubset@2, Rsubset@3

Evaluation Metrics and Baseline

Evaluation Metrics

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Key Baselines

- Existing training-free method
- Existing Zero-Shot CIR methods
- Compare across different scale VLM

Dataset	Domain	Metric
FashionIQ	Fashion images	R@10, R@50
CIRR	Real-world data	R@1, R@5, R@10, R@50, Rsubset@1, Rsubset@2, Rsubset@3

Comparison on FashionIQ (ViT L/14, 428M params)

In the CLIP L/14, we even achieve better than the previous SOTA

Method	Traning-Free	Average R@10	Average R@50
Pic2Word	X	24.70	43.70
SEARLE		27.61	47.90
LinCIR		26.28	46.49
CIReVL	V	28.55	48.57
LDRE		28.51	50.54
WeiMoCIR (Ours)		31.54	50.99

Comparison on FashionIQ (ViT G/14, 1.37B params)

Although the SOTA achieve much better results, we still outperformance than other training free apoach

Method	Traning-Free	Average R@10	Average R@50
Pic2Word	X	31.28	51.89
SEARLE		34.81	55.71
LinCIR		45.11	65.69
CIReVL	V	32.19	52.36
LDRE		32.49	55.46
WeiMoCIR (Ours)		37.03	57.29

Comparison on CIRR (ViT L/14, 428M params)

We get great performance at the smaller model in CIRR

Method	Traning-Free	R@1	R@5	R@10	R@50
Pic2Word	X	23.90	51.70	65.30	87.80
SEARLE		24.87	52.31	66.29	88.58
LinCIR		25.04	53.25	66.68	-
CIReVL	V	24.55	52.31	64.92	86.34
LDRE		26.53	55.57	67.54	88.50
WeiMoCIR (Ours)		30.94	60.87	73.08	91.61

Comparison on CIRR (ViT G/14, 1.37B params)

But, we still have the room for improvement on G/14

Method	Backbone	Traning-Free	R@1	R@5	R@10	R@50
Pic2Word	ViT G/14	X	30.41	58.12	69.23	-
SEARLE	ViT G/14		34.80	64.07	75.11	-
LinCIR	ViT G/14		35.25	64.72	76.05	-
CIReVL	ViT G/14	V	34.65	64.29	75.06	91.66
LDRE	ViT G/14		36.15	66.39	77.25	93.95
WeiMoCIR (Ours)	ViT G/14		31.04	60.41	72.27	90.89

Comparison with the training-free methods (ViT B/32, 151M params)

Method	Dataset	Average R@10	Average R@50
CIReVL	FashionIQ	28.29	49.35
LDRE	FashionIQ	24.81	45.63
WeiMoCIR (Ours)	FashionIQ	29.86	49.82

Method	Dataset	R@1	R@5	R@10	R@50
CIReVL	CIRR	23.94	52.51	66.00	86.95
LDRE	CIRR	25.69	55.13	69.04	89.90
WeiMoCIR (Ours)	CIRR	26.31	57.69	70.36	91.01

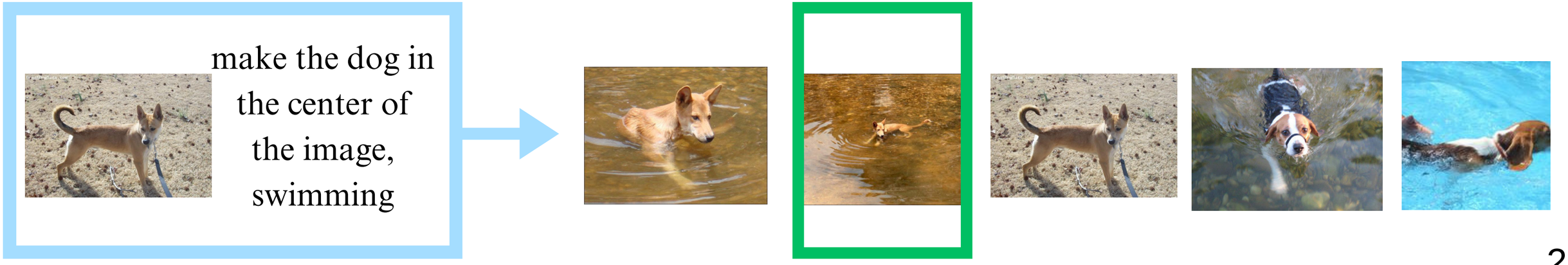
Qualitative results: Successful cases

- Text modifiers include color and style adjustments.

Qualitative results: Successful cases

- Text modifiers include color and style adjustments.

- Queries involve complex scene and action modifications.



Qualitative results: Failure cases

- Subtle Differences: Difficulty distinguishing fine-grained attributes.

Qualitative results: Failure cases

- Subtle Differences: Difficulty distinguishing fine-grained attributes.

Is more black with less graphics
It is black and has a simple print



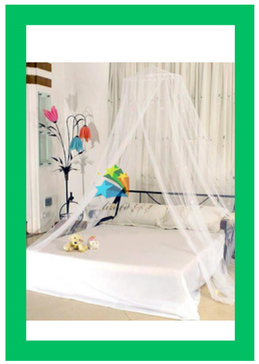



- Object Positioning: Struggles with relational queries.

The mattress is on the floor instead of on a bed





Impact of Different Pretrained VLMs

- Performance depends heavily on the alignment between VLM pretraining datasets and target CIR datasets.

CIRR			Recall@K				$Recall_{Subset}$@K		
Backbone	α	β	R@1	R@5	R@10	R@50	R@1	R@2	R@3
CLIP ViT L/14	0.80	0.10	30.94	60.87	73.08	91.61	58.55	79.06	90.07
CLIP ViT H/14	0.80	0.10	29.11	59.76	72.34	91.18	57.23	79.08	89.76
CLIP ViT G/14	0.80	0.10	31.04	60.41	72.27	90.89	58.84	78.92	89.64
BLIP w/ ViT-B	0.95	0.20	25.16	52.55	64.94	86.96	56.58	77.40	88.75
BLIP w/ ViT-B†	0.95	0.20	33.37	62.63	73.30	92.19	63.98	82.46	91.81
BLIP w/ ViT-B‡	0.95	0.20	**36.51**	**66.75**	**77.88**	93.45	**65.06**	**82.63**	**92.60**
BLIP w/ ViT-L	0.95	0.20	24.46	53.04	66.70	88.99	50.92	73.78	86.65
BLIP w/ ViT-L†	0.95	0.20	30.94	61.64	73.49	92.60	57.88	78.53	90.02
BLIP w/ ViT-L‡	0.95	0.20	32.07	63.08	75.28	**93.49**	58.63	79.13	90.53

† Finetuned on Flickr30k ‡ Finetuned on COCO

Effects of MLLM-Generated Captions

- Using multiple captions in most cases yields better results compared to a single caption.
- Combining captions provides a more complete description of image content.

Captions ($t_{n,r}$)	CLIP R@10	CLIP R@50	BLIP R@10	BLIP R@50
$t_{n,1}$	31.44	50.82	22.48	40.21
$t_{n,2}$	30.77	50.18	21.33	39.48
$t_{n,3}$	30.84	49.96	22.07	38.80
$t_{n,1} \cup t_{n,2}$	31.84	50.94	22.79	40.83
$t_{n,2} \cup t_{n,3}$	31.05	50.12	22.39	40.15
$t_{n,1} \cup t_{n,3}$	**31.77**	50.98	**22.95**	40.50
$t_{n,1} \cup t_{n,2} \cup t_{n,3}$	31.54	**50.99**	22.93	**41.00**

Impact of the MLLM-generated captions

- We found out that the best caption quality is located at the 1st one, the performance will drop compared to 1st captions.

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Conclusion

Key Contributions	Fusion	Combines image and text features for flexible query representation.
	Captions	MLLMs enrich database images with diverse semantic descriptions.
	Similarity	Balances query-to-image and query-to-caption matches for robust retrieval.

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Key Contributions	Fusion	Combines image and text features for flexible query representation.
	Captions	MLLMs enrich database images with diverse semantic descriptions.
	Similarity	Balances query-to-image and query-to-caption matches for robust retrieval.
Achieves		• Achieves ZS-CIR without additional training. • Simplifies workflows while delivering competitive results. • Adaptable to diverse tasks and datasets.

Code is available at
https://github.com/whats2000/WeiMoCIR

Future Work

Observation

- Performance at rank-50 is highly effective, indicating the method retrieves relevant candidates at a broader scale.
- However, refining results at the top-rank (eg. 1, 5) still requires improvement.

Proposed Solution

- Reranker to refine

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Proposed Solution

- Reranker to refine

Observation

- Incorporating textual descriptions improves retrieval performance by providing semantic context.
- Current captions are free-form and lack structured representation.

Proposed Solution

- Structured descriptions

Outline

Issue

- CIR Problem: Requires labor-intensive triplet collection.
- ZS-CIR Challenge: Most solutions still need pretraining on large datasets.
- Need: Training-free, scalable with model evolve.

Movtivation

- Avoid resource-intensive pretraining.
- Improve text-image alignment.
- Simplify and Efficiency retrieval with pre-trained models.

Method

- Fusion: Weighted text-image combination.
- Enhancement: Captions via MLLMs.
- Similarity: Combines query-to-image and query-to-caption.

Contribution

- Linear fusion of image and text.
- Introduces multimodal enhancement for retrieval.
- A new training-free ZS-CIR method.

Result

- Matches or surpasses pre-trained methods, especially small scale VLM
- MLLMs improve similarity scoring.

Future Work

- Improve high-rank results with rerankers.
- Utilize structured captions for better relevance scoring.

Compare with other method

Method	Fusion Approach	Focus	Training-Free	Handling Modalities
Pic2Word	Maps image → pseudo words	Query	x	Text-only
CIReVL	Caption + Text Modifier	Query	v	Text-dominant, limited visual context
LDRE	Diverse captions for expansion	Query Expansion	v	Expands queries via textual reasoning
WeiMoCIR	Weighted image + text fusion	Database + Query	v	Balances visual and textual relevance

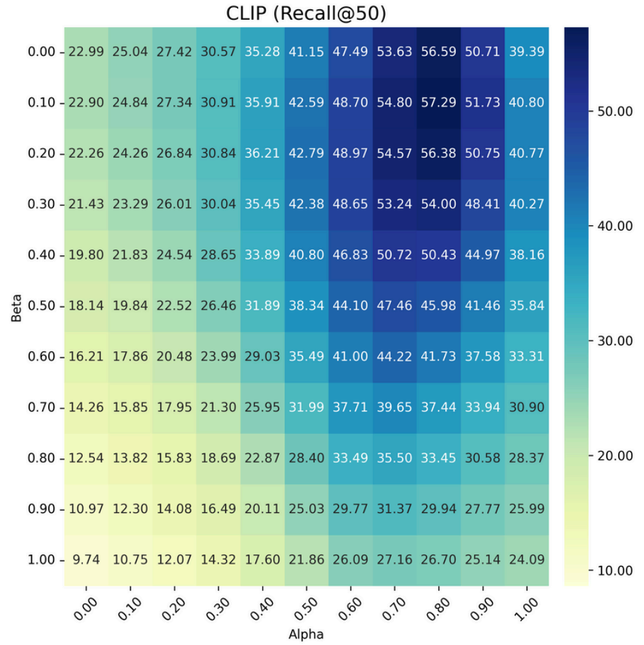
Effects of α and β on Performance

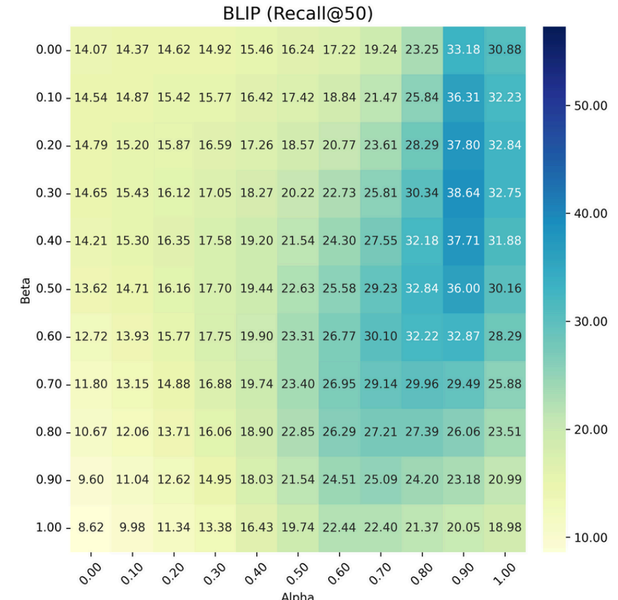
α (Query Modality Fusion)

- Balances visual and textual contributions.
- Higher α: More weight on text.
- Best performance observed with moderate to high α, emphasizing textual contributions.

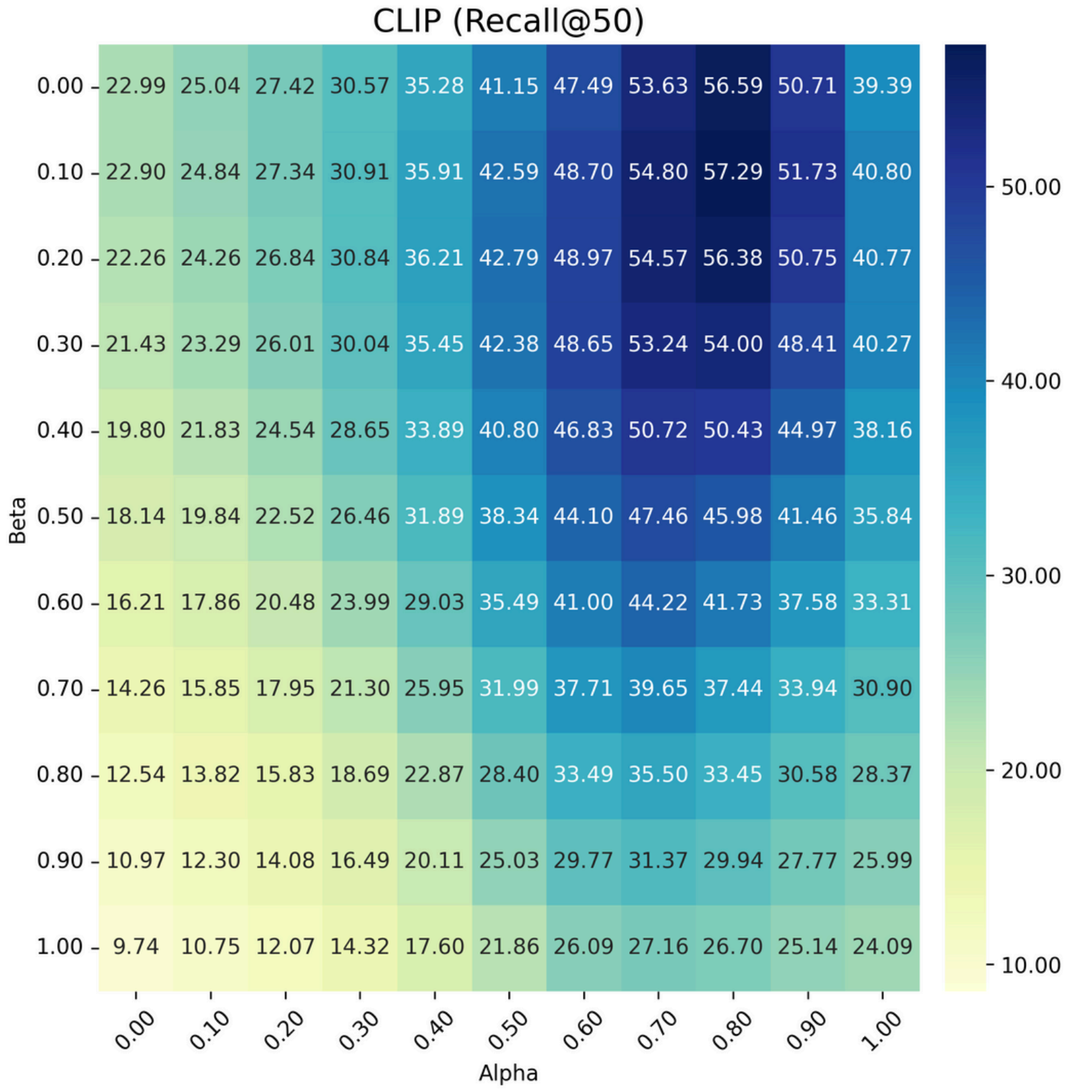
β (Similarity Weight)

- Balances query-to-image and query-to-caption similarities.
- Best performance was achieved with higher β, indicating the importance of caption-based information.





CLIP


CLIP (Recall@50)
Beta
Alpha
0.00 22.99 25.04 27.42 30.57 35.28 41.15 47.49 53.63 56.59 50.71 39.39
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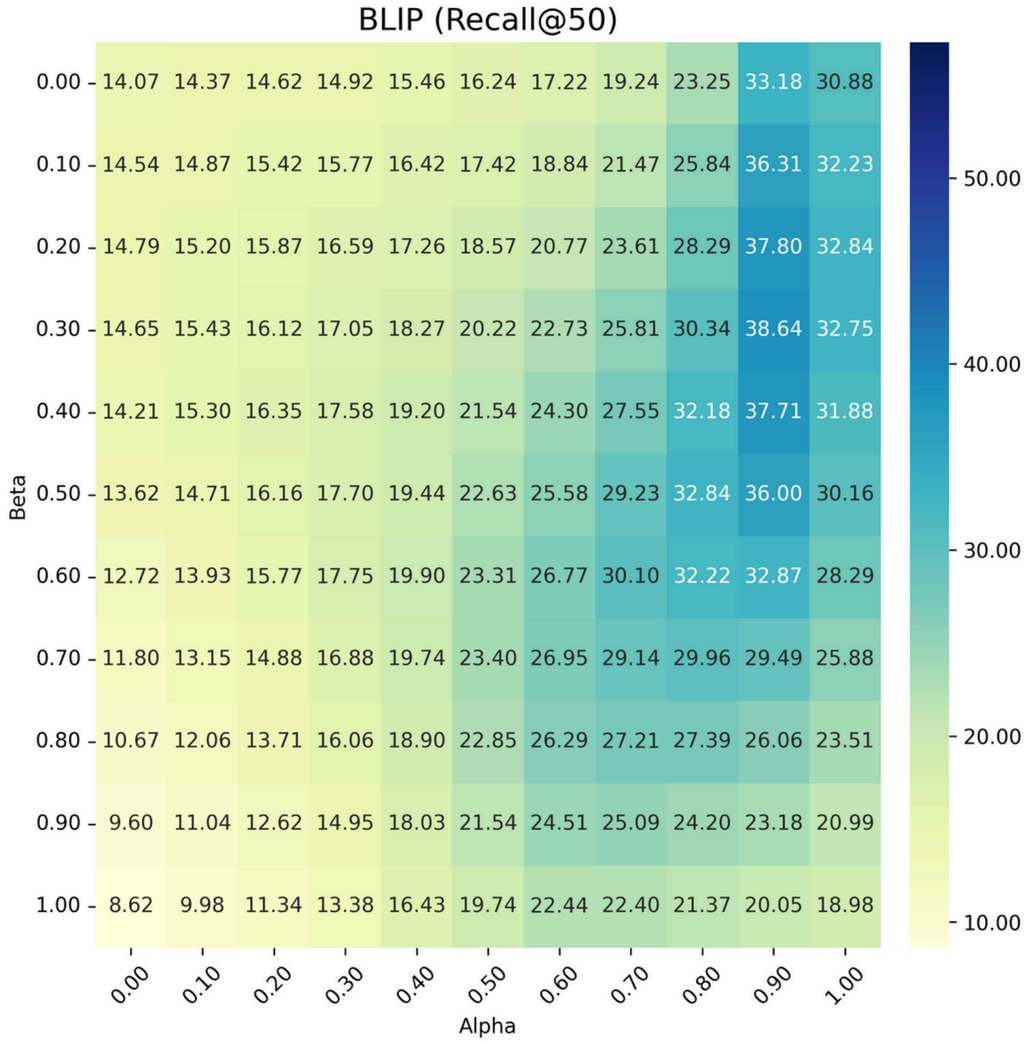
BLIP


BLIP (Recall@50)
Beta
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0.00 14.07 14.37 14.62 14.92 15.46 16.24 17.22 19.24 23.25 33.18 30.88
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