UNIVERSAL MULTI-MODALITY RETRIEVAL WITH ONE UNIFIED EMBEDDING SPACE

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ABSTRACT

This paper presents Vision-Language Universal Search (VL-UnivSearch), which builds a unified model for multi-modality retrieval. VL-UnivSearch encodes query and multi-modality sources in a universal embedding space for searching related candidates and routing modalities. To learn a tailored embedding space for multi-modality retrieval, VL-UnivSearch proposes two techniques: 1) Universal embedding optimization, which contrastively optimizes the embedding space using the modality-balanced hard negatives; 2) Image verbalization method, which bridges the modality gap between images and texts in the raw data space. VL-UnivSearch achieves the state-of-the-art on the multi-modality open-domain question answering benchmark, WebQA, and outperforms all retrieval models in each single modality task. It demonstrates that universal multi-modality search is feasible to replace the divide-and-conquer pipeline with a united model and also benefit per modality tasks. All source codes of this work will be released via Github.

1 INTRODUCTION

Although search engines primarily focused on textual data [Singhal et al., 2001], the information that would satisfy users’ search needs is ubiquitous to different modalities. A user query can be answered with the knowledge in variant formats, a text piece, or a picture. The growth of multi-media content has been one of the most notable trends on the internet [Mei et al., 2014]. Various studies have proved that users prefer more vivid multi-media content in search results [Datta et al., 2008].

Current multi-media search systems tackle this problem via divide-and-conquer. They conduct a search in individual modality, text, image, video, etc. [Bajaj et al., 2016; Grubinger et al., 2008; Kwiatkowski et al., 2019; Awad et al., 2021], and then fuse the retrieval results from various verticals together, e.g., using federated search and building another ranking layer on the top of individual modality search engine [Escalante et al., 2008; Grubinger et al., 2008]. As shown in Figure 1(a), each single-modality retrieval designs one or more models for searching related sources, and then the single-modality retrieval results are fused to satisfy the needs of multi-modality.

In this paper, we explore the potential of universal multi-modality retrieval to overcome the challenges in divide-and-conquer systems, which derives from the stage that fuses retrieval results from different modalities. Illustrated in Figure 1(b), universal multi-modality retrieval maps user queries and multi-modality sources to one universal embedding space and retrieves multi-modality candidates via one KNN search operation. As a result, the relevance modeling, cross-modality matching, and retrieval result weighting/fusion are done by one unified model.

More specifically, we focus on two modalities, text and image, and propose two techniques to build a Vision-Language Universal Search model (VL-UnivSearch): universal embedding optimization and image verbalization. When routing retrieved modalities, universal multi-modality retrieval models should regard each modality equally and calibrate the retrieval results according to the information need of users. VL-UnivSearch optimizes the universal embedding space with hard negatives [Xiong et al., 2021a] and balances the modalities of these negatives to alleviate the modality preference...
during retrieval. Furthermore, VL-UnivSearch comes up with an image verbalization method, which paraphrases the image facts in natural language to enhance the textural representations of images. It helps bridge the modality gap between images and texts in the raw data space.

To build a multi-modality retrieval benchmark, we leverage a multi-modality question answering (QA) benchmark WebQA (Chang et al., 2021) in our experiments and convert it to a standard open-domain QA setting, which retrieves candidates from multi-modality sources for user queries. Divide-and-conquer is an intuitive way to build a multi-modality retrieval system and we treat it as the oracle by pre-routing modality during retrieval. Our model, VL-UnivSearch, addresses the challenges that come from the divide-and-conquer pipelines by jointly modeling different single-modality retrieval and modality routing, achieving the state-of-the-art multi-modality retrieval performance, as well as outperforming baseline retrieval models in each single-modality scenario.

Our experiments show that VL-UnivSearch learns a tailored embedding space for both single-modality and multi-modality retrieval tasks. It eliminates the retrieval preference of different modalities and achieves better retrieval results by bridging vision-language modalities in the raw text space. All these experimental results show that learning one universal representation space from multi-modalities is starting to be more beneficial than a single-modality task with more than 5% improvements—pretraining representation model on multi-modality and our learning techniques can leverage the additional signals from different modalities, to overcome the modality boundary and provide better results in both multi-modality and single-modality setting.

2 Related Work

Document retrieval is a typical single modality retrieval task, which satisfies user information needs by returning related documents for a given query. The document retrieval task can be tackled with dense retrievers, which conduct efficient search by encoding queries and documents into an embedding space (Karpukhin et al., 2020; Xiong et al., 2021a; Lewis et al., 2020; Zhan et al., 2021; Li et al., 2021; Yu et al., 2021).

Existing vision-language research mainly focuses on the cross-modality retrieval tasks, such as MSCOCO (Chen et al., 2015) and Flickr30K (Young et al., 2014), which aim to conduct cross-modality matching and return candidates from a single modality. The vision-language models usually establish cross-modality interactions and calculate the similarity score between an image and a sentence, e.g. image captions (Radford et al., 2021; Jain et al., 2021; Srinivasan et al., 2021). Such interactions are built based on the semantic alignments between texts and image objects, which is distinct from the search relevance.

Recently, lots of work targets answering queries with multi-modality sources, which focuses more on evaluating the relevance between query and multi-modality sources (Hannan et al., 2020; Singh et al., 2021; Talmor et al., 2021; Chang et al., 2021). In these tasks, multi-modality retrieval is the first stage in QA systems to search sources to answer user queries (Chang et al., 2021; Chen et al., 2017). Instead of routing the queries to different modality sources for downstream modeling (Hannan et al., 2020; Talmor et al., 2021), WebQA (Chang et al., 2021) is built to retrieve information from attribute modality. WebQA also establishes a divide-and-conquer pipeline by searching sources...
from individual modalities and then fusing and reranking these retrieval results via a vision-language model. However, the divide-and-conquer pipeline brings more noise from divided retrieval systems and shows less effectiveness in fusing multi-modality retrieval results (Chang et al., 2021), making it difficult to build a realistic open-domain multi-modality question answering system.

Vision-language pretraining (VLP) has achieved success on lots of vision-language benchmarks (Upal et al., 2022; Han et al., 2020; Khan et al., 2021; Du et al., 2022). Similar to pretrained language models (Devlin et al., 2019), most VLP approaches employ a fusion encoder to learn multi-modality features by pretraining with masked token prediction and text-image matching tasks. They extract image features by object detection (Chen et al., 2019; Lu et al., 2019; Tan and Bansal, 2019; Su et al., 2020; Li et al., 2019; 2021a; Zhang et al., 2021; Cho et al., 2021; Hu et al., 2020; Gan et al., 2020) or directly encoding image features (Xu et al., 2021; Kim et al., 2021; Huang et al., 2021; Wang et al., 2021) and learn the semantic alignments between texts and images.

3 Universal Search Task

In this section, we formulate the universal multi-modality retrieval task and discuss its differences from two related tasks, single modality retrieval, and cross-modality retrieval.

Single Modality Retrieval. Single modality retrieval targets at searching related sources in a single modality space. Text passage retrieval (Xiong et al., 2021a) is a typical single-modality retrieval task, which searches candidates from the passage collection \( P = \{ P_1, ..., P_n \} \), according to the user query \( q \).

Cross Modality Retrieval. The cross-modality retrieval task contains two evaluation directions, including text-image retrieval and image-text retrieval. Given a text passage \( P_i \) or an image \( I_j \), these tasks require retrieval models to search candidates from a different modality collection of images \( I = \{ I_1, ..., I_m \} \) or text passages \( P = \{ P_1, ..., P_n \} \), which describe the same facts with \( P_i \) or \( I_j \), respectively.

Multi-Modality Retrieval. Given a query \( q \), the universal search task helps users uncover the information from multi-modality sources \( S = \{ P_1, ..., P_n, I_1, ..., I_m \} \).

Different from single modality and cross-modality retrieval tasks, multi-modality retrieval aims at returning relevant candidates from the multi-modality source \( S \). The retrieval results may consist of texts, images, or a mixture of them, based on the information needs of user query \( q \). Besides, multi-modality retrieval focuses more on relevance modeling between queries and multi-modality sources, single and cross-modality matching, and modality routing, making this task more challengeable than both single-modality and cross-modality retrieval tasks.

Previously, the divide-and-conquer pipeline can be used to build a multi-modality retrieval system, which leverages delicately designed retrieval models to search for candidates from each modality. Then it can use a linear weight layer or VLP model to fuse rerank these candidates, which usually becomes a challenge in the whole pipeline (Escalante et al., 2008; Chang et al., 2021).

4 UnivSearch via Unified Embedding

This section describes our vision-language universal retrieval (VL-UnivSearch). As shown in Figure 2, given a query \( q \) and multi-modality sources \( S = \{ P_1, ..., P_n, I_1, ..., I_m \} \), it directly encodes query \( q \), images \( I = \{ I_1, ..., I_m \} \) and text passages \( P = \{ P_1, ..., P_n \} \) in a unified embedding space and conducts retrieval by KNN search (Sec. 4.1).

Texts and images have different understanding mechanisms, making it difficult to tackle multi-modality tasks. But, both language and vision can be commonly translated as a type of mentalese to better communicate between different modules in our brains (Cavanagh, 2021), showing the necessity of building unified multi-modality representations and multi-modality interactions. To build a unified multi-modality retrieval system, VL-UnivSearch contrastively learns a universal embedding space by using hard negatives with balanced-modality sampling (Sec. 4.2) and bridging the modality gap via verbalizing the image features to paraphrase pixel semantics in the raw text space (Sec. 4.3).
4.1 Multi-Modality Dense Retrieval

VL-UnivSearch represents queries, images and passages with two encoders, TextEncoder and ImgEncoder. Specifically, the TextEncoder encodes textural data, such as query, image captions and text passages. And ImgEncoder encodes image pixels.

**Query Encoding.** VL-UnivSearch directly encodes the query $q$ to get its representation $h^q$:

$$h^q = \text{TextEncoder}(q).$$ (1)

**Text Passage Encoding.** To represent text passages, VL-UnivSearch also leverages the TextEncoder to encode the $i$-th passage $P_i$ as $h^P_i$:

$$h^P_i = \text{TextEncoder}(P_i).$$ (2)

**Image Encoding.** Different from text passages, the information of images can be described as pixel features and image caption texts. Thus, VL-UnivSearch encodes image pixel $I_j$ and image caption $C_j$ and then sums these embeddings to get the representation $h^I_j$ of $j$-th image:

$$h^I_j = \text{ImgEncoder}(I_j) + \text{TextEncoder}(C_j),$$ (3)

where the image representation is composed of the semantics of different modalities. The representations of images and text passages use the same TextEncoder to encode their textual information and bridge different modalities in the text space, which helps to build a universal embedding space for multi-modality retrieval.

**Multi-modality Source Retrieval.** The similarity score $f(q, s)$ of query $q$ and candidate $s \in S$ can be calculated:

$$f(q, s) = \cos(h^q, h^s),$$ (4)

where the $h^q$ and $h^s$ are the representations of $q$ and $s$. The efficient similarity calculation can be provided by FAISS\(^{1}\).

4.2 Universal Embedding Optimization

Then our VL-UnivSearch learns a universal embedding space through training with modality-balanced hard negatives, which calibrates the retrieval results of different modalities.

\(^{1}\)https://github.com/facebookresearch/faiss
Given the query \( q \) and its relevant candidate \( s^+ \in S \), the embedding space can be optimized by sampling hard negatives \( S^- \) and minimizing the following contrastive training loss:

\[
l(q, s^+, S^-) = -\log \frac{e^{f(q, s^+)/\tau}}{e^{f(q, s^+)/\tau} + \sum_{s^- \in S^-} e^{f(q, s^-)/\tau}}
\]

\[
= -\frac{f(q, s^+) - \log(e^{f(q, s^+)/\tau} + \sum_{s^- \in S^-} e^{f(q, s^-)/\tau})}{\tau}
\]

(5)

where \( \tau \) is the temperature to scale the similarity score and \( S^- = \{P_1^-, ..., P_k^-, I_1^-, ..., I_k^-\} \). \( S^- \) consists of 2k negatives sampled from the top-retrieved text passages and images.

As shown in Eq. 5 during training multi-modality encoders, we indeed maximize \( f(q, s^+) \) and minimize \( f(q, s^-) \), which aligns the related query-source pair and pulls the negatives away from the query. It is apparent that training with modality-imbalanced negatives stimulates the query conducts the smaller similarity scores with the majority modality of the sampled negatives, making the loss \( l(q, s^+, S^-) \) decrease easier. Thus, modality-balanced negative sampling is critical to make the multi-modality retrievers regard texts and images impartially and better coverage related multi-modality sources for the given query.

### 4.3 Image Verbalization for Expansion

Both textual matching and image paraphrasing are more easily to accomplish than modeling the relevance between different modalities, thus VL-UnivSearch verbalizes image pixel features to enhance the textual representations of images.

For the \( j \)-th image \( I_j \), we can detect the objections \( O = \{O_1, ..., O_l\} \) that appeared in the \( j \)-th image \( I_j \). Then we can get the regional features \( h_i^O \) and object class \( \hat{O}_i \) of the \( i \)-th object \( O_i \) in the detected objection set \( O \). VL-UnivSearch aims to generate verbalization \( V(I_j) \) for the \( j \)-th image \( I_j \) by paraphrasing the image facts among detected objects \( O \).

We can directly enrich image semantics in the text space by verbalizing the image with a caption:

\[
X_j^i = [CLS]; C_j; [SEP]; \hat{O}_1; ...; \hat{O}_l; [SEP]; h_1^O; ...; h_l^O,
\]

(6)

where : is the concatenation operation. These generated captions usually describe the facts among detected objects and ignore the alignments of mentioned entities/objects between image pixels and manually written captions. To tackle the challenge, we can generate query-style image verbalization by feeding \( I_j \)'s related query \( q_j \):

\[
X_j^q = [CLS]; q_j; [SEP]; C_j; [SEP]; h_1^O; ...; h_l^O,
\]

(7)

where [CLS] and [SEP] denote the start and end of a sentence. Then we utilize Masked Language Modeling (MLM) \cite{Devlin2019BERT} to optimize the vision-language models to generate the verbalization \( V(I_j) \) for image \( I_j \).

Finally, we expand the raw caption \( C_j \) by simply concatenating the generated image verbalization \( V(I_j) \) to get a reformulated image caption \( C_j^* \):

\[
C_j^* = C_j; [SEP]; V(I_j),
\]

(8)

where the reformulated caption is used to replace the raw caption \( C_j \) in Eq. 5 to get the representation of image \( I_j \) for multi-modality retrieval.

### 5 Experimental Methodology

This section describes the dataset, baselines, some vision language models used in our experiments, and implementation details.

**Dataset.** A multi-hop and multi-modal open domain question answering dataset WebQA \cite{Chang2021} is used in our experiments. The dataset contains images and passages that are crawled from Wikipedia and the general Web. In our experiments, we randomly sample 5,000 queries from the original training set of WebQA and use the development set for evaluation. All data statistics are
shown in Table 1. To build an open-domain setting, we collect 389,750 images and 787,697 texts as multi-modality retrieval sources. The image collection contains all images crawled in the WebQA dataset, while the text collection consists of the relevant passages of all 41,732 queries, which are Wikipedia passage snippets selected based on noun chunks that appeared in the question.

**Evaluation Metrics.** We use NDCG@$K$, MRR@$K$, Recall@20, and Recall@100 as the evaluation metrics. $K$ can be 10 and 20. Following previous work ([Bajaj et al., 2016](https://openai.com)), we regard MRR@10 as our main evaluation.

**Vision-Language Models.** In experiments, we employ two state-of-the-art vision-language models, VinVL ([Zhang et al., 2021](https://vinvl.org)) and CLIP ([Radford et al., 2021](https://clip.github.com)) to implement different retrieval models in our experiments. VinVL ([Zhang et al., 2021](https://vinvl.org)) inherits Oscar ([Li et al., 2020](https://oscar-project.com)) architecture, which extracts object tags and region features as image features, and learns cross-modal representations by learning semantic alignments between images and texts. Different from VinVL, CLIP ([Radford et al., 2021](https://clip.github.com)) utilizes a dual encoder to project images and texts in the same semantic space for computing their similarity scores and is trained on a large-scale dataset WebImageText that contains 400 million image-text pairs. It has shown strong effectiveness on cross-modality retrieval tasks.

**Baselines.** Our baselines contain single modality retrieval, divide-and-conquer model, and universal multi-modality retrieval. For single modality retrieval, we encode images with their corresponding textural captions and employ the unsupervised method BM25 and supervised dense retriever DPR ([Karpukhin et al., 2020](https://dpr-project.com)) as baselines. DPR is trained with NQ ([Kwiatkowski et al., 2019](https://nq-project.com)), which is similar to the textual source of WebQA. We show the zero-shot performance of DPR and continuously train it with inbatch and hard negatives to implement NQ-DPR and NQ-ANCE models. The divide-and-conquer model uses the two best uni-modality retrieval models, BM25 and CLIP-DPR, to search candidates from text passages and images, and then fuses these multi-modality retrieval results by ranking candidates with their uni-modality rank reciprocals. Moreover, we also pre-route the oracle modality for retrievers and search candidates from single modality sources, showing the upper bound of the divide-and-conquer model. We also build universal multi-modality retrieval baselines VinVL-DPR and CLIP-DPR by training VinVL and CLIP with inbatch negatives. All baselines encode images with the pixel features and image captions.

**Implementation Details.** During training VL-UnivSearch, we employ the text and image encoders from CLIP, truncate the text with max length of 77$^2$ and set batch size to 64, learning rate=$5e^{-6}$, max training epoch to 20, and the temperature hyperparameter $\tau = 0.01$. In our experiments, we sample two hard negatives of different modalities ($k = 1$) from retrieved Top 100 candidates using inbatch-trained VL-UnivSearch. All models are tuned with AdamW optimizer, evaluated per 500 steps, and early stop step as 5. More experimental details are shown in Appendix A.1.

## 6 Evaluation Results

In this section, we study the performance of VL-UnivSearch, its advantages on single-modality and multi-modality retrieval, and the effectiveness of embedding optimization strategies and image verbalization in multi-modality modeling.

### 6.1 Overall Performance

The multi-modality retrieval performance of different models is shown in Table 2.
Table 2: Multi-Modality Retrieval Performance of Different Models. VinVL-DPR, CLIP-DPR, NQ-DPR and BERT-DPR are trained with inbatch-sampled negatives, while NQ-ANCE is trained with hard negatives sampled from the retrieval results of NQ-DPR. DPR and CLIP show their zero-shot retrieval performance.

| Setting      | Model            | MRR@10 | NDCG@10 | MRR@20 | NDCG@20 | Rec@20 | Rec@100 |
|--------------|------------------|--------|---------|--------|---------|--------|---------|
|             |                  |        |         |        |         |        |         |
| Single Modality | BM25             | 53.75  | 49.00   | 54.10  | 51.72   | 68.16  | 80.69   |
|              | DPR              | 22.72  | 20.06   | 23.14  | 21.79   | 32.78  | 45.43   |
|              | CLIP w. img caption | 18.16  | 16.76   | 19.60  | 18.27   | 27.97  | 39.83   |
|              | BERT-DPR         | 42.16  | 39.57   | 42.76  | 42.26   | 60.85  | 77.10   |
|              | NQ-DPR           | 41.88  | 39.65   | 42.44  | 42.35   | 61.71  | 78.57   |
|              | NQ-ANCE          | 45.54  | 42.05   | 45.93  | 43.83   | 58.42  | 69.31   |
| Divide-Conquer | VinVL-DPR       | 22.11  | 22.92   | 22.80  | 25.41   | 46.27  | 62.82   |
|              | CLIP-DPR         | 37.35  | 37.56   | 37.93  | 40.77   | 69.38  | 85.53   |
|              | BM25 & CLIP-DPR  | 42.27  | 41.58   | 42.79  | 44.69   | 73.34  | 87.50   |
|              | BM25 & CLIP-DPR (Oracle Modality) | 61.05  | 58.18   | 61.37  | 60.45   | 80.82  | 90.83   |
| UnivSearch   | CLIP w. img feature | 10.59  | 8.69    | 10.80  | 9.52    | 14.32  | 20.23   |
|              | VinVL-DPR       | 38.14  | 35.43   | 38.74  | 37.79   | 53.89  | 69.42   |
|              | CLIP-DPR        | 48.73  | 46.27   | 49.24  | 49.06   | 69.83  | 86.43   |
|              | VL-UnivSearch   | 62.54  | 59.39   | 62.83  | 61.29   | 80.37  | 89.42   |

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Our VL-UnivSearch outperforms all baseline models with more than 7% improvement in ranking performance, recalls more than 6% relevant sources for downstream vision-language models, and even shows better performance than the oracle divide-and-conquer model. Such significant improvements illustrate that VL-UnivSearch is effective to build a multi-modality retrieval system by mapping multi-modality sources in one universal embedding space, which unifies the cross-modality matching and modality routing during retrieval.

Among all baseline models, textural retrieval models usually show strong effectiveness, which converts the cross-modality retrieval task into textural retrieval and bridges both texts and images in the text space. Moreover, other cross-modality retrieval models usually encode images with caption and pixel features using SOTA vision-language models, but still underperform BM25. It illustrates that fusing retrieval results from different modalities is still challengeable for multi-modality retrieval. CLIP-DPR can alleviate such fusion challenges by achieving better retrieval performance, while it shows less effectiveness in reconciling multi-modality retrieval fusion with single-modality source recalling. On the contrary, VL-UnivSearch can deal with this problem by continuously fine-tuning text and image encoders through our universal embedding optimization strategy and image verbalization strategy, which help to learn a more tailored embedding space to build a universal retrieval system. The following experiments further explore how VL-UnivSearch bridges images and texts in a universal embedding space for multi-modality retrieval.

6.2 Ablation Studies

The ablation studies are conducted to study the multi-modality retrieval effectiveness. We also evaluate how VL-UnivSearch performs with single-modality trained models on individual modality.

As shown in Table 3, we evaluate the retrieval effectiveness of different vision-language models, VinVL-DPR and CLIP-DPR, in both single modality training and universal multi-modality training scenarios. They are trained with inbatch negatives on single-modality and multi-modality retrieval tasks. In the single modality training setting, we fine-tune vision-language models with a group of queries that only contain related candidates in text modality or image modality. Our multi-modality training setting uses all queries to train these vision-language models and equally samples inbatch negatives from different modality sources.

CLIP shows strong effectiveness than BERT and VinVL on per modality retrieval tasks, showing its effectiveness in representing images and text for retrieval. During image representation modeling, the image captions usually play a critical role in cross-modality matching, while image features show less effectiveness in representing image semantic information for retrieval. Such a phenomenon mainly derives from the shallow understanding of existing vision representation models, which contradicts the task requirements of questing answering and makes the cross-modality retrieval more difficult. It is noticeable that image features indeed help to achieve much better retrieval performance for the CLIP model, demonstrating the necessity of leveraging both image captions and image features in representing images.
Table 3: Retrieval Performance of Different Ablation Models. MRR@10 is used as the evaluation metric.

| Model                          | Retrieval Performance | Retrieved Image (%) |
|-------------------------------|-----------------------|---------------------|
|                               | Text      | Image    | Multi    |          |
| **Single Modality Models**    |           |          |          |          |
| BERT-DPR                      | 37.09     | 52.34    | -        |          |
| VinVL-DPR w/o caption         | -         | 3.67     | -        |          |
| VinVL-DPR w/o img feature    | -         | 51.56    | -        |          |
| VinVL-DPR                     | 25.00     | 48.68    | -        |          |
| CLIP-DPR w/o caption          | -         | 17.74    | -        |          |
| CLIP-DPR w/o img feature     | -         | 58.17    | -        |          |
| CLIP-DPR                      | 52.57     | 59.95    | -        |          |
| **Universal Multi-Modality Models** | |          |          |          |
| VinVL-DPR w/o img feature    | 29.01     | 46.55    | 36.13    |          |
| VinVL-DPR                     | 29.95     | 49.65    | 38.14    |          |
| CLIP-DPR w/o img feature     | 51.47     | 57.36    | 50.33    |          |
| CLIP-DPR                      | 51.67     | 60.60    | 48.73    |          |
| VL-UnivSearch                 | **60.91** | **65.61**| **62.54**|          |

Table 4: Effectiveness of Different Hard Negative Training Strategies. These hard negative trained models start from inbatch trained ones and are continuously fine-tuned with different numbers of hard negatives. The MRR@10 score and the image ratio of Top 10 retrieved candidates are shown to evaluate retrieval effectiveness.

| Sampling                       | Retrieval Performance | Retrieved Image (%) |
|-------------------------------|-----------------------|---------------------|
|                               | Text      | Image    | Multi    |          |
| **Inbatch Training**          |           |          |          |          |
| DPR (Random)                  | 51.67     | 60.60    | 48.73    | 26.82    |
| Balanced Inbatch              | 52.24     | 59.99    | 49.88    | 30.35    |
| **Hard Negative Training**    |           |          |          |          |
| Only Texts                    | 54.92     | 52.88    | 36.26    | 91.74    |
| Only Images                   | 55.85     | **66.51**| 33.49    | 1.97     |
| 2 Texts & 1 Image             | 59.18     | 65.15    | 61.64    | 49.53    |
| 1 Text & 2 Images             | 57.86     | 66.23    | 61.20    | 47.88    |
| ANCE (Random)                 | 59.85     | 64.80    | 61.72    | 50.01    |
| Balanced Inbatch              | **60.58** | 65.21    | **62.29**| 49.11    |

VL-UnivSearch shows its advantages by outperforming all single-modality trained retrieval models on both text and image retrieval tasks, demonstrating that multi-modality modeling indeed benefits per single modality task. In multi-modality modeling, CLIP-DPR achieves better performance on both text and image retrieval scenarios than CLIP-DPR w/o image feature. It demonstrates that image features provide additional features to help multi-modality models distinguish images and texts, which thrives on the single-modality task. On the contrary, the multi-modality retrieval performance of CLIP-DPR is decreased, which mainly lies in the task transformation from single-modality to multi-modality. The distinct retrieval performance illustrates that fusing retrieval results from different modalities may be one of the most important reasons to limit the effectiveness of existing multi-modality retrieval models.

### 6.3 Learning Unified Representations with Balanced Hard Negative Sampling

In this subsection, we further evaluate our universal embedding optimization strategies by comparing different negative choosing methods.

As shown in Table 4, we start from the inbatch trained CLIP model, continuously fine-tune it using different numbers of hard negatives and show their performance on the retrieval tasks of different modalities. Our experimental results show that the inbatch trained retrieval model prefers to return texts than images as the ranking results, even the image-answerable queries take a larger portion (about 51.6%) in the training data. It illustrates that textual clues are easier to be used than image clues to distinguish the related sources.
Then, we further train models with hard negatives sampled from single modality negatives. Such a training strategy pushes the queries away from these hard negatives and extremely searches sources from a different modality. Using the negatives sampled from different modalities achieve more convincing performance, especially the balanced sampling method, which further demonstrates that balancing the negative sampling from different modalities is critical to building a universal multi-modality retrieval model and alleviating model preference or bias in retrieving candidates from different modality sources.

Finally, we visualize the embedding space of different retrieval models in Figure 3 using t-SNE. As shown in Figure 3(b) and Figure 3(c) when the retrieval models are trained with solo text and image negatives, the query embeddings are concentrated and respectively assigned closer to images and texts in the embedding space. This behavior will help to win a lower contrastive training loss during training but lead to undesired discrimination during retrieval from different modality sources, showing the necessity of training multi-modality retrieval models with balanced hard negatives. After training with balanced hard negatives sampled from different modalities, VL-UnivSearch learns more distinguished vision-language representations, which satisfies the goal of learning a uniform embedding space during contrastive training (Wang and Isola, 2020). In such an embedding space, both texts and images are separately assigned in different areas of the whole embedding space, and queries are almost located around the embedding clusters of images and texts, which are adjusted to determine which modality sources are returned by retrieval models.

6.4 BRIDGING CROSS-MODALITY MATCHING WITH IMAGE VERBALIZATION

VL-UnivSearch proposes an image verbalization model to bridge the text and image matching by generated image captions or queries. In this experiment, we present the retrieval model performance using different image verbalization strategies.

From previous experimental results (Sec. 6.2), image features are critical in representing images, while the image semantics are harder to comprehend by existing vision encoders. Thus, VL-UnivSearch tries to verbalize the image features by extracting the objects that appeared in the image and describing the facts among detected object classes (Zhang et al., 2021). The image verbalization results paraphrase image pixel facts in natural language and help to enhance the textural representations of images by expanding image verbalization results to image captions.

As shown in Table 5, image verbalization methods show their effectiveness by consistently improving the multi-modality retrieval performance, demonstrating that these verbalization methods can help learn more effective representations for images. It is mentionable that our verbalization methods can also benefit text retrieval performance. The main reason may lie in that the image verbalization results make the textual representations of images more informative and help the text encoder distinguish the related candidate from the multi-modality sources in the text embedding space during training. Compared with the verbalized captions, VL-UnivSearch usually achieves better performance with the verbalized queries, which are generated by aligning the semantics between image captions and image features. It showcases that our query verbalization method is effective to provide useful information for image representations. Moreover, some additional experiments are provided to study the effectiveness of different image verbalization methods. We first show the effectiveness of the
Table 5: Performance of Multi-Modality Retrieval Models with Different Image Verbalization Methods. All models are evaluated with MRR@10.

verbalized queries with different manual caption lengths in Appendix [A.2] and then conduct some case studies in [A.3] to explore the characteristics of different verbalization models.

7 CONCLUSION

This paper proposes VL-UnivSearch, which encodes both queries and multi-modality sources in a universal embedding space for retrieval. Our experiments show that the boundary of different modalities can be broken by unified multi-modality modeling of our VL-UnivSearch, making our model achieve the state-of-the-art on multi-modality tasks and also outperform single modality retrievers.

REFERENCES

George Awad, Asad A Butt, Keith Curtis, Jonathan Fiscus, Afzal Godil, Yooyoung Lee, Andrew Delgado, Jesse Zhang, Eliot Godard, Baptiste Chocot, et al. 2021. Trecvid 2020: A comprehensive campaign for evaluating video retrieval tasks across multiple application domains.

Payal Bajaj, Daniel Campos, Nick Craswell, Li Deng, Jianfeng Gao, Xiaodong Liu, Rangan Majumder, Andrew McNamara, Bhaskar Mitra, Tri Nguyen, et al. 2016. Ms marco: A human generated machine reading comprehension dataset.

Patrick Cavanagh. 2021. The language of vision*. Perception, 50(3):195–215.

Yingshan Chang, Mridu Narang, Hisami Suzuki, Guihong Cao, Jianfeng Gao, and Yonatan Bisk. 2021. Webqa: Multihop and multimodal qa.

Danqi Chen, Adam Fisch, Jason Weston, and Antoine Bordes. 2017. Reading Wikipedia to answer open-domain questions. In Proceedings of ACL, pages 1870–1879.

Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C Lawrence Zitnick. 2015. Microsoft coco captions: Data collection and evaluation server.

Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. 2019. Uniter: Learning universal image-text representations.

Jaemin Cho, Jie Lei, Hao Tan, and Mohit Bansal. 2021. Unifying vision-and-language tasks via text generation. In Proceedings of ICML, pages 1931–1942.

Ritendra Datta, Dhiraj Joshi, Jia Li, and James Z Wang. 2008. Image retrieval: Ideas, influences, and trends of the new age. ACM Computing Surveys (Csur), (2):1–60.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of NAACL-HLT, pages 4171–4186.

Yifan Du, Zikang Liu, Junyi Li, and Wayne Xin Zhao. 2022. A survey of vision-language pre-trained models.
Hugo Jair Escalante, Carlos A Hérnadez, Luis Enrique Sucar, and Manuel Montes. 2008. Late fusion of heterogeneous methods for multimedia image retrieval. In Proceedings of the 1st ACM international conference on Multimedia information retrieval, pages 172–179.

Zhe Gan, Yen-Chun Chen, Linjie Li, Chen Zhu, Yu Cheng, and Jingjing Liu. 2020. Large-scale adversarial training for vision-and-language representation learning. In Proceedings of NeurIPS.

M Grubinger, P Clough, A Hanbury, and H Müller. 2008. Overview of the imageclef 2008 photographic retrieval task. In Working Notes of the 2008 CLEF Workshop. Aarhus, Denmark.

Kai Han, Yunhe Wang, Hanting Chen, Xinghao Chen, Jianyuan Guo, Zhenhua Liu, Yehui Tang, An Xiao, Chunjing Xu, Yixing Xu, et al. 2020. A survey on visual transformer.

Darryl Hannan, Akshay Jain, and Mohit Bansal. 2020. Manymodalqa: Modality disambiguation and QA over diverse inputs. In Proceedings of AAAI, pages 7879–7886.

Xiaowei Hu, Xi Yin, Kevin Lin, Lijuan Wang, Lei Zhang, Jianfeng Gao, and Zicheng Liu. 2020. Vivo: Surpassing human performance in novel object captioning with visual vocabulary pre-training.

Zhicheng Huang, Zhaoyang Zeng, Yupan Huang, Bei Liu, Dongmei Fu, and Jianlong Fu. 2021. Seeing out of the box: End-to-end pre-training for vision-language representation learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12976–12985.

Aashi Jain, Mandy Guo, Krishna Srinivasan, Ting Chen, Sneha Kudugunta, Chao Jia, Yinfei Yang, and Jason Baldridge. 2021. Mural: multimodal, multitask retrieval across languages.

Vladimir Karpukhin, Barlas Oguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense passage retrieval for open-domain question answering. In Proceedings of EMNLP, pages 6769–6781.

Salman Khan, Muzammal Naseer, Munawar Hayat, Syed Waqas Zamir, Fahad Shahbaz Khan, and Mubarak Shah. 2021. Transformers in vision: A survey. ACM Computing Surveys (CSUR).

Wonjae Kim, Bokyung Son, and Ildong Kim. 2021. Vilt: Vision-and-language transformer without convolution or region supervision. In Proceedings of ICML, pages 5583–5594.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, Kristina Toutanova, Llion Jones, Matthew Kelcey, Ming-Wei Chang, Andrew M. Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: A benchmark for question answering research. Transactions of the Association for Computational Linguistics, pages 452–466.

Mike Lewis, Marjan Ghazvininejad, Gargi Ghosh, Armen Aghajanyan, Sida I. Wang, and Luke Zettlemoyer. 2020. Pre-training via paraphrasing. In Proceedings of NeurIPS.

Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang. 2019. Visualbert: A simple and performant baseline for vision and language.

Wei Li, Can Gao, Guoqiang Niu, Xinyan Xiao, Hao Liu, Jiachen Liu, Hua Wu, and Haifeng Wang. 2021a. UNIMO: Towards unified-modal understanding and generation via cross-modal contrastive learning. In Proceedings of ACL, pages 2592–2607.

Xiujuan Li, Xi Yin, Chunyuan Li, Pengchuan Zhang, Xiaowei Hu, Lei Zhang, Lijuan Wang, Houdong Hu, Li Dong, Furu Wei, et al. 2020. Oscar: Object- semantics aligned pre-training for vision-language tasks. In European Conference on Computer Vision, pages 121–137. Springer.

Yizhi Li, Zhenghao Liu, Chenyan Xiong, and Zhiyu Liu. 2021b. More robust dense retrieval with contrastive dual learning. In Proceedings of the 2021 ACM SIGIR International Conference on Theory of Information Retrieval, pages 287–296.

Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. 2019. Vilbert: Pretraining task-agnostic vision-linguistic representations for vision-and-language tasks. In Proceedings of NeurIPS, pages 13–23.
Tao Mei, Yong Rui, Shipeng Li, and Qi Tian. 2014. Multimedia search reranking: A literature survey. ACM Computing Surveys (CSUR), (3):1–38.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. 2021. Learning transferable visual models from natural language supervision. In Proceedings of ICML, pages 8748–8763.

Christopher Scialvolo, Zexuan Zhong, Jinhyuk Lee, and Danqi Chen. 2021. Simple entity-centric questions challenge dense retrievers. In Proceedings of EMNLP, pages 6138–6148.

Hrituraj Singh, Anshul Nasery, Denil Mehta, Aishwarya Agarwal, Jatin Lamba, and Balaji Vasan Srinivasan. 2021. MIMOQA: Multimodal input multimodal output question answering. In Proceedings NAACL-HLT, pages 5317–5332.

Amit Singhal et al. 2001. Modern information retrieval: A brief overview. IEEE Data Eng. Bull., (4):35–43.

Krishna Srinivasan, Karthik Raman, Jiecao Chen, Michael Bendersky, and Marc Najork. 2021. Wit: Wikipedia-based image text dataset for multimodal multilingual machine learning. In Proceedings of SIGIR, pages 2443–2449.

Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. 2020. VL-BERT: pre-training of generic visual-linguistic representations. In Proceedings of ICLR.

Alon Talmor, Ori Yoran, Amnon Catav, Dan Lahav, Yizhong Wang, Akari Asai, Gabriel Ilharco, Hannaneh Hajishirzi, and Jonathan Berant. 2021. Multimodalqa: complex question answering over text, tables and images. In Proceedings of ICLR.

Hao Tan and Mohit Bansal. 2019. LXMERT: Learning cross-modality encoder representations from transformers. In Proceedings of EMNLP, pages 5100–5111.

Shagun Uppal, Sarthak Bhagat, Devamanyu Hazarika, Navonil Majumder, Soujanya Poria, Roger Zimmermann, and Amir Zadeh. 2022. Multimodal research in vision and language: A review of current and emerging trends. Information Fusion, pages 149–171.

Tongzhou Wang and Phillip Isola. 2020. Understanding contrastive representation learning through alignment and uniformity on the hypersphere. In Proceedings of ICML, pages 9929–9939.

Zirui Wang, Jiahui Yu, Adams Wei Yu, Zihang Dai, Yulia Tsvetkov, and Yuan Cao. 2021. Simvlm: Simple visual language model pretraining with weak supervision.

Lee Xiong, Chenyan Xiong, Ye Li, Kwok-Fung Tang, Jialin Liu, Paul N. Bennett, Junaid Ahmed, and Arnold Overwijk. 2021a. Approximate nearest neighbor negative contrastive learning for dense text retrieval. In Proceedings of ICLR.

Wenhua Xiong, Xiang Lorraine Li, Srinivasa Iyer, Jingfei Du, Patrick S. H. Lewis, William Yang Wang, Yashar Mehda, Scott Yih, Sebastian Riedel, Douwe Kiela, and Barlas Oguz. 2021b. Answering complex open-domain questions with multi-hop dense retrieval. In Proceedings of ICLR.

Haiyang Xu, Ming Yan, Chenliang Li, Bin Bi, Songfang Huang, Wenming Xiao, and Fei Huang. 2021. E2E-VLP: End-to-end vision-language pre-training enhanced by visual learning. In Proceedings of ACL, pages 503–513.

Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. 2014. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. Transactions of the Association for Computational Linguistics, pages 67–78.

Shi Yu, Zhenghao Liu, Chenyan Xiong, Tao Feng, and Zhiyuan Liu. 2021. Few-shot conversational dense retrieval. In Proceedings of SIGIR.

Jingtao Zhan, Xiaxin Mao, Yiquan Liu, Min Zhang, and Shaoping Ma. 2021. Optimizing dense retrieval model training with hard negatives. In Proceedings of SIGIR.
Pengchuan Zhang, Xiaojun Li, Xiaowei Hu, Jianwei Yang, Lei Zhang, Lijuan Wang, Yejin Choi, and Jianfeng Gao. 2021. Vinvl: Revisiting visual representations in vision-language models. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5579–5588.
A APPENDIX

A.1 ADDITIONAL EXPERIMENT DETAILS

This subsection describes additional implementation details. In our experiments, we employ two pretrained vision-language models, VinVL and CLIP, and the pretrained language model, BERT to implement different retrieval models.

**VinVL-DPR.** For VinVL variant models, we first detect the image objects and extract corresponding region features following VinVL\(^3\). Then we concatenate image captions and image region features as inputs to feed into VinVL models and get the image representations. We initialize VinVL with the checkpoint trained on the MSCOCO image retrieval task and continuously train the model on the WebQA dataset with inbatch negatives. During training, we set the batch size to 32, learning rate=$2e^{-5}$, accumulate step as 1, and max training epoch to 30. We truncate the query, image captions, textual passages, and image region features with max lengths of 70, 70, 200, and 50.

**CLIP-DPR.** For training CLIP-DPR, we start from the ViT-B/32 version of CLIP and continuously train CLIP-DPR on the WebQA dataset with inbatch negatives. We truncate texts with the max length of 77, accumulate step as 1, and set the batch size to 64, learning rate=$5e^{-6}$, max training epoch to 20, and the temperature hyperparameter $\tau = 0.01$. The cosine annealing strategy is used to schedule the learning rate.

**BERT-DPR.** We initialize our retriever with the bert-base-uncased checkpoint, which is provided by Hugginface Transformers\(^4\). During training, we set the batch size to 32, learning rate=$5e^{-5}$, accumulate step as 1, and max training epoch to 30. We truncate the query, textual passages, and image captions with max lengths of 70, 200, and 70.

**NQ-DPR/NQ-ANCE.** NQ-DPR and NQ-ANCE start from the NQ trained DPR model (Karpukhin et al., 2020), which uses a dual encoder architecture to encode queries and documents. Other experimental settings keep the same with BERT-DPR. Besides, NQ-ANCE is tuned with the negatives sampled from the Top 100 retrieved candidates.

**Image Verbalization.** The image verbalization models are used to generate captions or potentially related questions. Our experiments use the VinVL model trained on the MSCOCO image caption task (Zhang et al., 2021) to verbalize images.

We can first generate captions as image verbalization by setting generated tokens up to 20 and beam size to 5. For the caption generation, we feed the labels and region features of the detected object as inputs. During training the query generation model, we concatenate the image-related query, image caption, and image regional features as the input. Then we randomly mask the tokens in the query and train vision-language models to fill in the masked positions. We truncate the query, image captions, and image region features with the max lengths of 40, 30, and 50, respectively. The mask probability is set to 0.15.

A.2 IMAGE VERBALIZATION PERFORMANCE WITH DIFFERENT CAPTION LENGTHS

In this subsection, we evaluate the effectiveness of our image verbalization method with different caption lengths in Figure\(^4\).

We group the queries into three categories according to the caption length of the query-related image and calculate the average MRR@10 score for each query group. These ratios are 42.33%, 36.84%, and 20.83% of the short, medium, and long query length groups.

The experimental results show that our query generation method mainly helps improve the retrieval effectiveness on the queries of short length and medium length, illustrating that these generated queries can provide some crucial textual clues in image representations of shorter captions. These expanded text clues help retrieval models better understand image semantics, more effectively represent images via enhanced textual information, and conduct cross-modality matching more easily. Moreover, the queries in the medium caption length group achieve the best performance, because the image captions of medium lengths can cover more necessary text clues for generating a more informative query.

[^3]: https://github.com/microsoft/scene_graph_benchmark
[^4]: https://github.com/huggingface/transformers
Figure 4: Performance of Image Verbalization with Different Caption Lengths. The query lengths of short, medium and long query groups are in the sections of \([0, 10), [10, 20),\) and \([20, +\infty).\)

Table 6: Image Verbalization Cases.

| Query: Does a Minnetonka Rhododendron flower have petals in a cup shape? |
| Manual Caption: 2020-05-08 15 17 05 Minnetonka Rhododendron flower along Tranquility Court in the Franklin Farm section of Oak Hill, Fairfax County, Virginia Minnetonka Rhododendron flower along Tranquility Court in the Franklin Farm section of Oak Hill, Fairfax County, Virginia |
| Verbalized Caption: a purple flower with green leaves and purple flowers. |
| Verbalized Query: what shape are the petals of the minnetonka rhododendron flower? |

| Query: Are the heads of Iranian women covered in traditional clothing? |
| Manual Caption: Iranian family, gathered together wearing traditional clothes - Nishapur - Nowruz2014 Iranian family, gathered together wearing traditional clothes |
| Verbalized Caption: a group of people in costumes standing in a park. |
| Verbalized Query: how many people are wearing hats in the group of iranian family members? |

| Query: At the 1928 Amsterdam Olympics, what is the maximum number of buttons that you can get on the Egyptian men’s uniform? |
| Manual Caption: Egyptian athletes bij OS Amsterdam 1928 - Egyptian Olympic athletes, Amsterdam 1928 (6941436605) http://www.spaarnestadphoto.nl/component/option,com memorix ... |
| Verbalized Caption: a group of men in suits and hats standing in a field. |
| Verbalized Query: did all the men in the egyptian olympic athletes wear the same type of caps? |

| Query: What water-related object is sitting in front of the Torre del Reloj? |
| Manual Caption: Torre del Reloj de la Plaza Colón de Antofagasta (1) |
| Verbalized Caption: a water fountain in front of a clock tower. |
| Verbalized Query: is the fountain in front of the clock tower at la plaza de reloj taller than |

| Query: What color is the facade of bakery Sattin et Fils in Rheinfelden, France? |
| Manual Caption: Rheinfelden-FR-08-boulangerie Sattin-01 |
| Verbalized Caption: a red storefront on a city street corner. |
| Verbalized Query: how many potted plants are outside of the boulangerie sattin? |

| Query: Does the Durham Cathedral in England have any trees outside of it? |
| Manual Caption: Durham Cathedral, July 2014 (04) Durham Cathedral, Durham, County Durham, England |
| Verbalized Caption: a large building with two towers and a tree in front of it. |
| Verbalized Query: are there any trees near durham cathedral which are taller than the cathedral? |

A.3 Case Studies on Different Image Verbalization Methods

This part showcases some image verbalization cases in Table 6. We randomly sample queries that can be answered by images and show the manual captions, verbalized captions, and verbalized queries of the query-related images.

Overall, these cases can be categorized into two groups according to the lengths of manual captions. The first three cases are more informative to describe the image facts among mentioned objects, which can be directly used in query-image matching. On the contrary, the manual captions in the last three cases are written by the most representative object that appeared in the images, making it difficult to distinguish the related images only according to these manual captions.
VL-UnivSearch employs two image verbalization methods to enhance the textural semantics of images. Generating image captions is the most intuitive way to paraphrase images with some general image objective classes. Nevertheless, these pre-defined objective classes may be useless during retrieval, because the entities are critical to retrieving related sources in a question-answering system (Sciavolino et al., 2021). Different from these verbalized captions, the verbalized queries are usually more informative and meaningful. They specify the image objects by copying entity names from the manual captions, such as the names of person, place, and building. These entities can be directly matched with the given queries, which benefits cross-modality matching.