# A APPENDIX - Video Evaluation

## A.1 Video Search

VDMS provides full support for video storage and operations, in a similar way it does for images. This includes support for encoding, decoding, and transcoding of *mp4*, *avi*, and *mov* containers, as well as support for *xvid*, *H.263* and *H.264* encoders. This is supported through the Visual Compute Module that provides an abstraction layer on top of OpenCV [4] and *libffmpeg* [17]. All operations supported for images in VDMS are also supported at the video and frame level of the API. On top of that, there are a number of video-specific operations that are supported, such as the interval operations, enabling users to retrieve clips at different frames-per-second (FPS) versions of the video.

We evaluate the performance and scalability of the video management capabilities offered by VDMS. Handling video in a general way is a complex task. Some of this complexity comes from the existence of a variety of open and proprietary implementations, different encoding techniques and container formats, and different parameters of the video itself that are application-dependent, like frames per second, lossy compression, etc. When it comes to video, ad-hoc solutions have a large number of parameters that can be tuned. Together with that, there is no system that enables transactional operations over videos files in the way VDMS does. Because of this, we focus our efforts on understanding variations in the performance of VDMS and its scalability, rather than comparing it to a baseline that would not represent a fair comparison for either of the systems.

All this functionality is provided and integrated with the rest of the metadata API as part of the comprehensive VDMS interface. This makes it possible for users to interact with metadata and video in a transactional manner, enabling users to run queries like: "Retrieve all the videos where there is a *lake* with probability higher than 0.86, converting all videos to *H.264 mp4* of size 224x224". Appendix shows a sample of how this query would be implemented using the VDMS API [4]. In particular, this functionality was used internally to select a subset of videos with the right licenses for a video summarization application.

To the best of our knowledge, there is no solution that can provide all the functionality mentioned above, behind a single interface that also allows users to interact with images and metadata. Implementing a baseline, like we did for images, is significantly more complex due to the parametrization of video encodings and containers, as explained at the beginning of this section. For this reason, we chose to make a study using VDMS in various scenarios, and analysis of scalability and the impact of having the overhead of VDMS' Request Server in the overall access time and throughput.

Figure 8 shows the analysis of different queries aimed at retrieving a video using the VDMS interface. We show how VDMS throughput increases when serving a video object as the number of simultaneous clients increases, as well as the overhead operations introduced in the overall query execution time. The figure on the left compares the number of video transaction per second (i.e., number of videos returned per second) when different operations are executed as part of the transaction. The upper-bound of this would be simply returning the video as-is (without running any encoding/decoding or operation), represented by the red line. This query is the upper-limit because it essentially translates to reading the video from the file-system and sending it over a TCP/IP socket, without any other overhead or operations.

```
"FindEntity"{
    "class": "autotag",
    "constraints": {
        "name": ["==", "lake"]
    }
    "_ref" : 1
},
"FindVideo":{
    "container": "mp4",
    "codec": "h.264",
    "link": {
        "ref":1,
        "constraints": {
            "prob": [">=", 0.86]
        }
    }
    "operations": [{
        "type": "resize",
        "height": 1080,
        "width":  1920,
    }]
}
```

Listing 2: Sample Query for Video - The query expresses the following: Find all videos connected to the autotag *lake* with probability higher than 0.86, apply a resize operation to make the video 1920×1080, and convert to "mp4" file, using H.264 encoding.

We also run a set of other queries that involve, showed in Figure 8: (a) running a resize operation on the video and, consequently, decoding and encoding operations as well (blue line), (b) transcoding, meaning the use of a different container and encoder than the one originally used (yellow line), and (c) both resize and transcoding. Note that the resize operation (blue and green lines) performs a downsize, which translates in less data being sent over the wire. This is specially noticeable when supporting 32 simultaneous clients, where the

[4] https://github.com/{Not shown during submission}

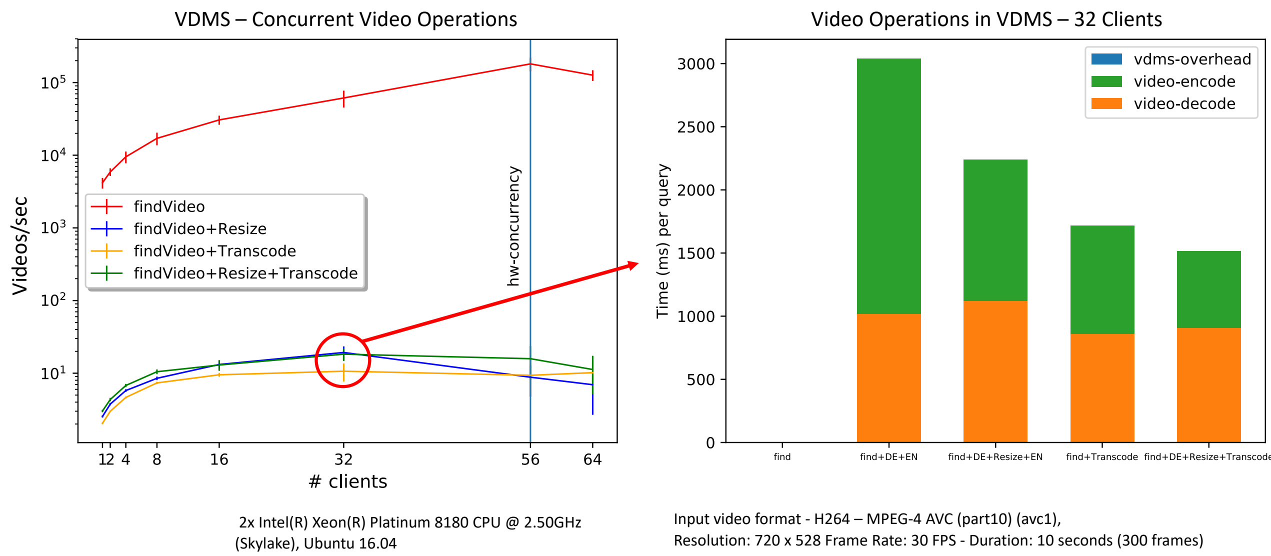


Figure 8: Analysis of video operations. The left figure shows the video throughput (videos per sec) as the number of concurrent clients increase and the right figure breaks down the different components of the queries using 32 clients.

system provides more videos per second due to sending less data to the client, when compared to just transcoding and not resizing (yellow line). We can see that the system performs best when using all the physical cores, and this can be attributed to the compute-bound nature of video encoding, decoding, and processing.

It is important to note an almost 3 orders of magnitude drop in performance when including operations as part of the query. We wanted to understand where most of the time was spent on the queries, and optimize the Request Server and Visual Compute Module if necessary. For this, we run the experiment shown at Figure 8 (right) which breaks down the different components of the queries. This figure shows that more than 97% of the query execution is spent on encoding/decoding operations, which is well-known to be a compute intensive operation [23]. On the one hand, this result shows that VDMS barely introduces any overhead. On the other hand, this result means a limit on the opportunities for optimization for video queries given that biggest time factors are accounted by encoding/decoding, which is outside the scope of VDMS. This result was the call to action for one optimization we will include in future releases of VDMS, which involves using *ffmpeg* C++ API to limit the number of frames being encoded/decoded when possible. This functionality will prevent encoding/decoding to happen on all frames when users only need to retrieve a subset of the frames in the video.

# B APPENDIX - Similarity Search Evaluation

## B.1 Similarity Search

Another key differentiating factor of VDMS is that it allows the creation of indexes for high-dimensional feature vectors and the insertion of these feature vectors associated with entities, images, and/or videos. Feature vectors are intermediate results of various machine learning or computer vision algorithms when run on visual data. Feature vectors are also known as *descriptors* or *visual descriptors*. We use these terms interchangeably. These descriptors can be classified, labeled, and used to build search indexes. There are many in-memory libraries that are designed for this task [13, 19].

Using the VDMS API, users can manage feature vector indexes, query previously inserted elements, run a k-nearest neighbor search (*knn*), and express relationships between existing images or descriptors and the newly inserted descriptors. By natively supporting descriptors and *knn*, VDMS allows out-of-the-box classification functionalities for many applications [5].

For this work, and as part of a comprehensive image search implementation, we have used 4096-dimensional descriptors extracted from every image (and first frame of every video) from the YFCC100M dataset and created a collection of these feature vectors in VDMS to perform similarity search (i.e., find images that are *similar* to an query (input) image). *Similarity* in this particular case is defined as closeness in a 4096-dimensional space using euclidean distance as the metric.

The process of loading descriptors in VDMS is simple. First, the user has to create a DescriptorSet, using a single command. At creation of the DescriptorSet, the dimensionality of the descriptors is specified, together with the desired indexing method and the desired metric for computing distances (Euclidean Distance, *L2*, or Inner Product, *IP*). Once the DescriptorSet is created, descriptors can be inserted to the set. After the descriptors are inserted, a similarity search can be performed.

Figure 9 shows 3 examples of a query image (on the left), and images returned as *similar* by VDMS. The input is a descriptor generated after a query image. The *query input* descriptor is sent to VDMS as part of the query, VDMS uses that descriptor to find similar ones, and retrieves the images associated with those *similar* descriptors. We show this as an example of the functionality and to depict how the feature vectors provided by the dataset can be used, but we also provide an analytical approach to the trade-off between accuracy and execution time in our system. It is important to note that the accuracy of the results is entirely tied to the quality of the descriptors chosen by the applications. The quality of the similarity result will be tied to the quality of the descriptor extraction that the application is using.

As mentioned before, VDMS provides different levels of customization of the indexes created for a descriptor set, that includes the indexing techniques and the metric for similarity. These different indexing techniques come with different trade-offs in terms of speed of search and accuracy of the computation. VDMS aims to provide functionality that is agnostics to application-specific techniques, enabling features that are generic to visual data processing applications. Figure 10 shows an analysis at the different indexing techniques provided by VDMS and its trades-off between accuracy and query execution speed, for a single threaded client. For this evaluation, we query the 10 closest neighbors (k = 10), and compute accuracy using recall at 4 (r_k = 4) (i.e. percentage of the top 4 ground-truth results that is present within the top 10 computed neighbors). We average the query execution time and accuracy for 100 queries (nq = 100). The *flat* index (red line) implements exact search and represents ground-truth, which explain why the accuracy is always 100% in the plot on the right. The other indexes implement *approximate search*, which trades-off between accuracy and speed of search [13, 19]. We have also tried the *ivfflat* index (inverted file index), as well as *LSH*-based indexes using a different number of bits per descriptor [6]. Results show how *ivfflat* is the fastest option but it comes with a trade-off of about 30% loss in accuracy, while simple brute-force search is among the slowest options at the expenses of 100% accuracy, meaning exact search.

Another important trade-off to be made is with respect to space efficiency: The DescriptorSet can grow very large and expensive to load and manage. In this particular case, 4096-dimensional descriptors for 100M elements translates into 1TB of data, only in raw floating-point data alone (without accounting for any metadata or indexes associated with it). This component is very important for the overall analysis on which index structure to use because a large set of descriptors may not fit in memory and thus cause a pressure on the IO system while retrieving descriptors for computing distance. This can severely impact the overall query execution time. When the DescriptorSet grows significantly large, it may be worth trading off accuracy for speed and space. Figure 11 shows the different indexes and their size in disk. These indexes already contain all the descriptors (or a quantized version of them in the case of LSH [6]), and can be loaded in memory directly when it fits. Note how, because of quantization of the descriptors, *LSH* provides a significantly lower space foot print, which can be a great option for large collections of descriptors when accuracy is not a main factor. It is not uncommon to sacrifice accuracy as images and videos are captured using a noise sensor (i.e., the camera), and an approximate search in many cases can provide the necessary accuracy for applications to achieve their goals.

[5] https://github.com/{Not shown during submission}

[6] https://github.com/facebookresearch/faiss/wiki/Faiss-indexes

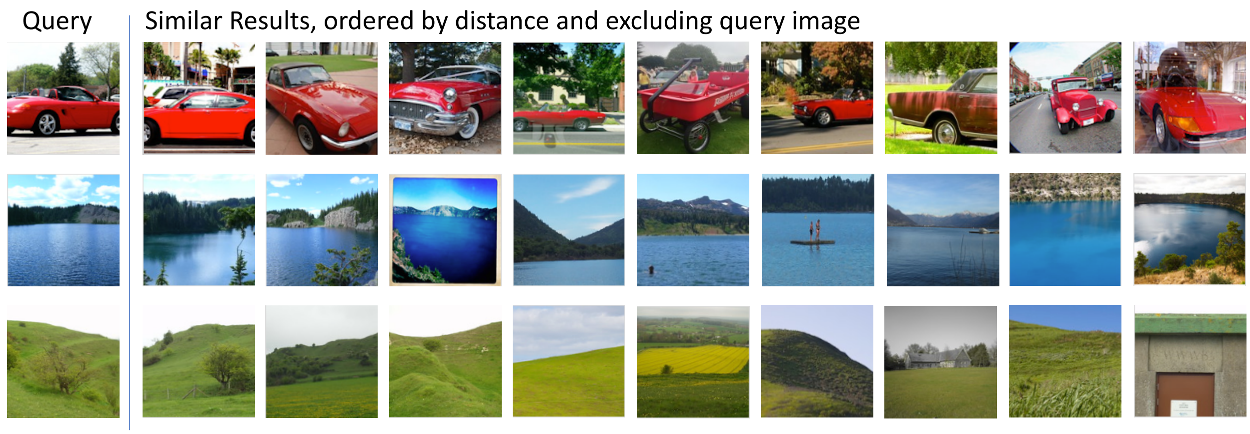


Figure 9: Sample Results of Similarity Search

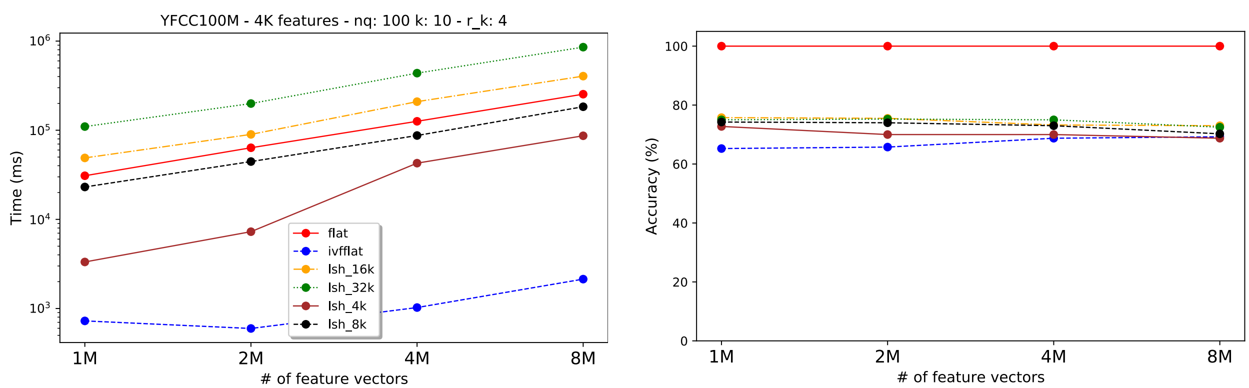


Figure 10: Feature Vector Evaluation: Trade-off between query execution speed and accuracy of the results, using ground-truth data for computing accuracy. For this evaluation, we query the 10 closest neighbors (k = 10), and compute accuracy using recall at 4 (r_k = 4) (i.e. percentage of the top 4 ground-truth results that is present within the top 10 computed neighbors). We average the query execution time and accuracy for 100 queries (nq = 100).

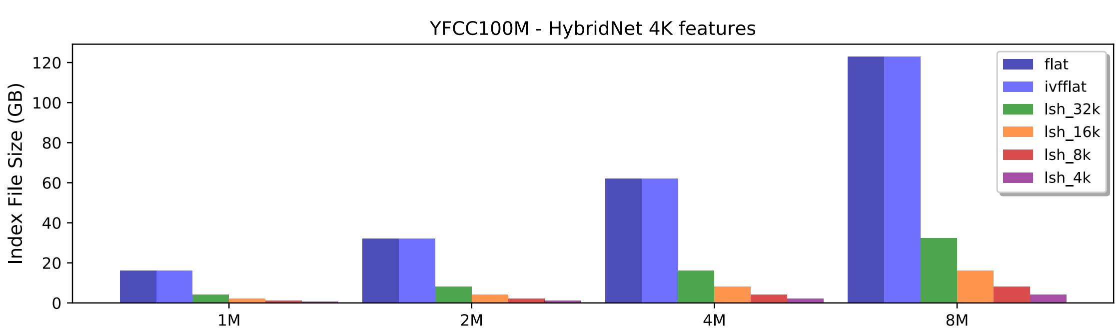


Figure 11: Feature Collection Size in Disk

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