VDMS: Efficient Big-*Visual*-Data Access for Machine Learning Workloads

Luis Remis *
Intel Labs

Vishakha Gupta-Cledat
Intel Labs

Christina R. Strong
Intel Labs

Ragaad Altarawneh
Intel Labs

Abstract

We introduce the Visual Data Management System (VDMS), which enables faster access to big-*visual*-data and adds support to visual analytics. This is achieved by searching for relevant visual data via metadata stored as a graph, and enabling faster access to visual data through new machine-friendly storage formats. VDMS differs from existing large scale photo serving, video streaming, and textual big-data management systems due to its primary focus on supporting machine learning and data analytics pipelines that use visual data (images, videos, and feature vectors), treating these as first class entities. We describe how to use VDMS via its user friendly interface and how it enables rich and efficient vision analytics through a machine learning pipeline for processing medical images. We show the improved performance of 2x in complex queries over a comparable set-up.

1 Introduction

Visual computing workloads performing analytics on video or image data, either off-line or streaming, have become prolific across a wide range of application domains. This is in part due to the growing ability of machine learning techniques to extract information out of the visual data which can subsequently be used for informed decision making. The insights this information can provide depend on the application: a retail vendor might be interested in the amount of time shoppers spend in front of a specific product, while a medical expert might want to see the effect of a specific treatment on the size of a tumor.

Despite this rich and varied usage environment, there has been very little research on the management of visual data. Most of the current storage solutions are an ad-hoc collection of tools combined with custom scripts to tie them together, unique not only to a specific discipline but often to individual researchers. For example, consider an ML developer constructing a pipeline for extracting brain tumor information from existing brain images in a classic medical imaging use case. This requires assigning consistent identifiers for the scans and adding their metadata in some form of relational or key-value database. If the queries require search over some patient information, then patients have to be associated with their brain scans. Finally, if the ML pipeline needs images that are of a size different than the stored ones, there is additional compute diverted towards preprocessing after the potentially larger images are fetched. All these steps require investigation of different software solutions that provide various functionalities that can then be stitched together with a script for this specific use case. Moreover, if the pipeline identifies new metadata to be added for the tumor images, most databases make it hard to evolve the schema on the fly. Not only do these ad hoc solutions make replicating experiments difficult, they do not scale well to real-world applications. Addressing the storage and retrieval of visual data necessitates a complete overhaul of the storage architecture, preferably using emerging breakthroughs in heterogeneous memory and storage for efficiency.

*Corresponding author - `luis.remis@intel.com`

Workshop on Systems for Machine Learning and Open Source Software at NIPS 2018, Montréal, Canada.

We present the Visual Data Management System (VDMS)[4], an Open Source project designed to enable efficient access of visual data. Since visual data often contains rich metadata (such as objects, locations, and time), VDMS stores this information in a high performance graph database. Using this metadata, VDMS can quickly identify which data is relevant to a given query. Additionally, VDMS uses a custom library to store and retrieve visual data, which provides an interface for machine friendly formats as well as traditional formats. These new formats are designed to support applications that are often interested in specific areas of images or videos, particularly when the individual object is large.

While there are a number of big-data frameworks [11, 12], systems that can be used to store metadata [8, 7], and systems that manipulate a specific category of visual data [2, 1], VDMS can be distinguished from them on the following aspects:

- *Design for analytics and machine learning*: by targeting visual data for use cases that require manipulation of visual information and associated metadata,
- *Ease-of-use*: By defining a common API that allows applications to combine their complex metadata searches with operations on resulting visual data, and together with full support for feature vectors, VDMS goes beyond the traditional SQL or OpenCV level interfaces that do one or the other. Given our focus on enabling machine learning, we also provide a client API in Python.
- *Performance*: We show how a unified system such as VDMS can outperform an ad-hoc system constructed with well-known discrete components. Because of the capabilities we have built into VDMS, it handles complex queries significantly better than the ad-hoc system without compromising the performance of simple queries.

2 Design and Implementation

VDMS implements a client-server design. The VDMS Server handles client requests concurrently and coordinates request execution across the metadata and data components in order to return a unified response. The metadata component is the Persistent Memory Graph Database (PMGD). The data component is our custom library, the Visual Compute Library (VCL). The VCL enables machine friendly enhancements to visual data. VDMS and its components are fully available as open source tools [2].

Persistent Memory Graph Database: Recent developments in persistent memory technologies like 3D XPoint [5] promise storage elements providing nearly the speed of DRAM and the durability of block-oriented storage. To provide an efficient storage solution addressing the increasing popularity of connected data and applications that benefit from graph like processing, we have designed and implemented an in-persistent-memory graph database, PMGD, optimized to run on a platform equipped with persistent memory. PMGD provides a property graph model of data storage with the traditional atomicity, consistency, isolation, and durability properties expected from databases. The graph model makes it very suitable for the data model and access patterns shown by visual metadata. With its natural ability to extend the schema very easily (due to the use of a property graph model), we can support new developments in machine learning that can lead to enhancements to existing metadata over time. The specific details on how the data structures are optimized for persistent memory, and the performance comparison with other graph databases is on-going work that will be publish separately.

Visual Compute Library: The VCL was designed to provide an interface through which users can interact with visual data. For traditional formats, the interface is an abstraction layer over OpenCV. However, it also provides a way to use novel formats that are better suited for visual analytics: a novel, array-based lossless image format. This format is built on the array data manager TileDB [10] and is well suited for images that are used in visual analytics. The VCL currently provides limited support for videos but we are enhancing its capabilities as part of our future work. Feature vector support is provided through an implementation based on high-dimensional sparse arrays, also using TileDB, which contains both storage and search functionality over feature vectors. In addition, the VCL provides a wrapper for another high-dimensional index implementation, Facebook's Faiss [6].

[2]https://github.com/IntelLabs/{vdms, pmgd, vcl}

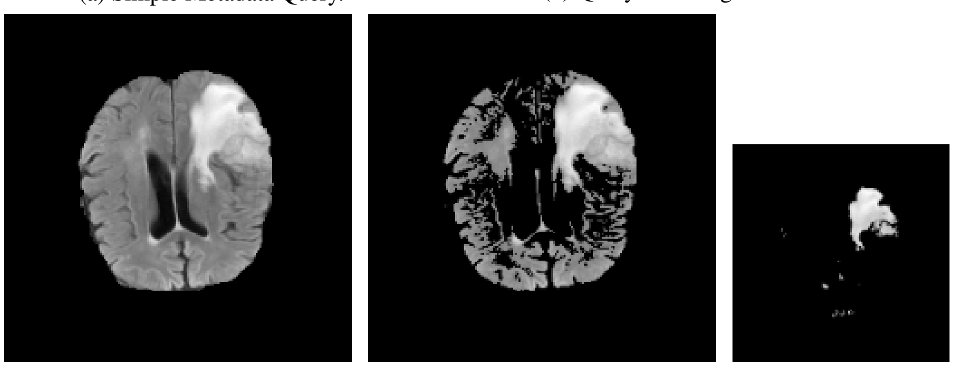
```python
import vdms

db = vdms.VDMS()
db.connect("localhost")

# Get information about patients over 85

query = """
[
   {
      "FindEntity" : {
         "class" : "patient",
         "constraints": { "age_at_initial": [">=", 85] },
         "results" : {
            "list" : [ "bcr_patient_barc",
                       "gender", "age_at_initial"]
         }
      }
   }
]"""

response, images = db.query(query)
vdms.aux_print_json(str(response))
```

```
[
    {
        "FindEntity": {
            "status": 0,
            "entities": [
                {
                    "bcr_patient_barc": "TCGA-76-4928-0",
                    "gender": "FEMALE",
                    "age_at_initial": 85
                },
                {
                    "bcr_patient_barc": "TCGA-12-1600-0",
                    "gender": "MALE",
                    "age_at_initial": 86
                }
            ],
            "returned": 2
        }
    }
]
```

(a) Simple Metadata Query.

```python
query = """
[
    "FindImage" : {
        "operations": [ {
                "type": "threshold",
                "value": 128
            }],
        "constraints": {
            "number": ["==", 85]
        },
    }
  }, {
     "FindImage" : {
        "operations": [ {
                "type": "resize",
                "height": 150,
                "width": 150
            },{
                "type": "threshold",
                "value": 128
            }],
        "constraints": {
            "number": ["==", 85]
        },
    }
  }
] """
```

(b) Query involving visual transformations.



(c) Original image (left) and the result of query in (b)

Figure 1: Snapshot of a Python notebook with sample queries

Request Server: Developers and users of machine learning frameworks and data science applications favor simpler interfaces to access and process data and cannot be expected to deal with two different ways of interacting with information (metadata and visual data) instead of focusing on the algorithmic parts of their pipelines. VDMS takes care of coordinating client requests across the metadata and the data as well as efficiently manages multiple clients through its Request Server component, by implementing a JSON-based API. It decomposes the command into metadata and data requests, invokes the relevant calls behind the scene, and returns a coherent response to the user after applying any additional operations (explained in the next section).

3 VDMS API

One of our goals with VDMS was to define an API that is easy to use. Our API explicitly predefines certain visual primitives associated with images, videos, and feature vectors. In addition, while we use a graph database to store our metadata, the API is not graph specific. We have paid particular attention to hide the complexities of our internal implementation and up-level the API to a JSON-based API[3], which is very popular across various application domains. We understand that by defining a new JSON-based API we had to trade-off expressiveness (compared to SPARQL or Gremlim) for the ability to design native support for visual data, but we believe that, as development of VDMS evolves, we will be able to achieve similar levels of expressiveness compared to more mature query languages. We have developed Python and C++ client library to provide a simple query function that accepts a JSON string with commands and an array or vector of blobs.

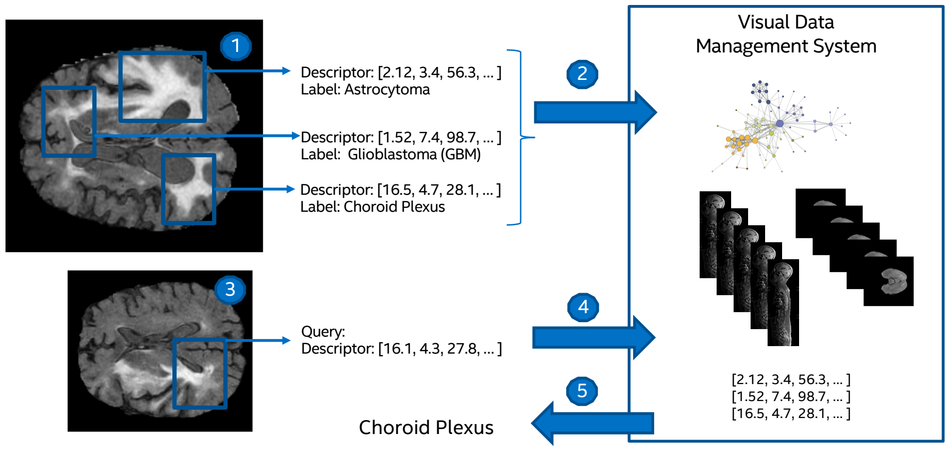


Figure 2: Feature Vectors natively supported in VDMS

We use a medical imaging dataset as a driving example, and use it here to showcase our API. More details about this use case are discussed in Section 4. Figure 1 shows a snapshot from a Jupyter Notebook with two simple queries. Figure 1a shows a simple metadata query where information about properties of patients matching some specific characteristics (admitted with 85 years of age or more) is used to constrain the search. The returned JSON structure shows 2 patients found in the database. Note that in this examples the queries are expressed as plain strings to help the reader understand its structure. In real applications, the queries are structured using the preferred method or library for handling JSON structures (e.g. Python dictionaries or jsoncpp in C++).

Figure 1b shows a query involving visual transformations. In this case, the query is looking for an image with a certain *id* value, and expects VDMS to return the image twice: once with a thresholding transformation (e.g., zero out all pixels less than a threshold), and the second time after applying a threshold and then resizing it. 1c shows the image originally inserted in VDMS (left), along with the returned images corresponding to the query in 1b. Adding new operations to VDMS is easy, as our software architecture encapsulates all operations in VCL, and any new operation can use or wrap around OpenCV, which is used internally.

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 or visual objects. Feature vectors are intermediate results of various machine learning or computer vision algorithms when run on visual data. These vectors can be labeled and classified to build search indexes, and there are many in-memory libraries that are designed for this task [9, 6]. Using the VDMS API, users can manage feature vector indexes, query previously inserted elements (images), run a k-nearest neighbor search (knn) and express relationships between existing images or feature vectors and the newly inserted feature vectors. By natively supporting feature vectors and knn, VDMS allows out-of-the-box classification functionalities for many applications. Figure 2 shows an example of how this functionality can be integrated in a medical imaging analytics pipeline: (1) A feature vector is extracted from an bounding box in a brain image and labeled; (2) the feature vector is inserted together with all the associated metadata (type of cancer, for example) and a link to the original image. (3) A new feature vector is extracted from a new image, (4) a query to VDMS is issued to classify that feature vector based on the indexed features in VDMS, and (5) VDMS can respond to the query with the label associated to that feature vector. Note that, even if the example is

[3]https://github.com/IntelLabs/vdms/wiki/API-Description

based on the medical images used for the performance evaluation, this methodology is applicable in many other contexts and use cases, such as face detection and matching. More details about the JSON API for this functionality can be found on our Github wiki page.

4 Medical Imaging Use Case

Standards for medical images, such as DICOM and NIfTI, were developed to assist in transmitting medical images along with their associated metadata. This metadata, consisting of patient information and often including treatments, can be used together with the images themselves in machine learning applications to gather insights. This makes medical imaging an excellent use case to demonstrate the metadata query and data pre-processing capabilities offered by VDMS. It also helps us explain how queries can be made increasingly complex to give more detailed information, finding the most relevant subset of patients for focused analyses.

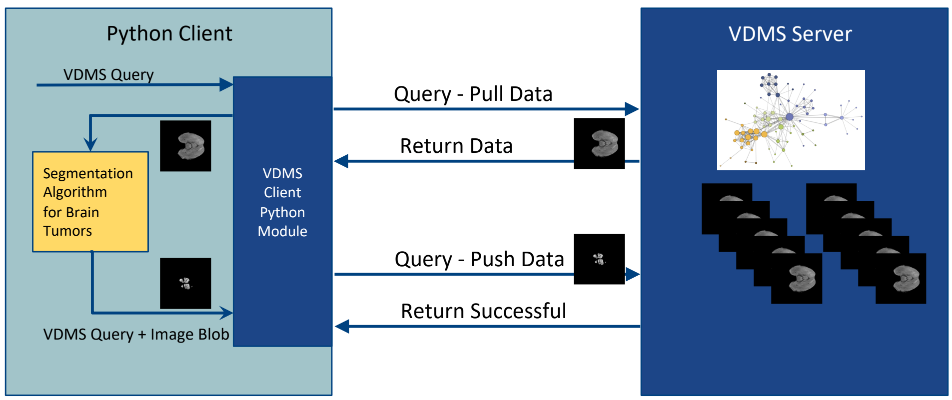


Figure 3: Segmentation pipeline to find brain tumors in existing patient brain scans

We implemented a pipeline for a medical imaging use case that processes brain scans. This pipeline feeds brain images to a convolution neural network (using U-Net) that runs a segmentation, the results of which are pushed back to storage for future use, as shown in Figure 3. We use The Cancer Image Archive dataset [3] for both metadata and image information (DICOM files).

We present our findings after performing three queries based on both metadata and visual data (brain scans) that are basic building blocks for running the pipeline in Figure 3. All queries return a resized (downsampled) version of the image that matched the requirement of the input layer of the CNN.

The three queries are:

1. **Query 1**: retrieve a single image from a brain scan, search by its unique name, and apply pre-processing operations: Simple case where a single command on the API is used.
2. **Query 2:** retrieve a complete brain scan (155 images) from a particular patient, and apply pre-processing operations: Involves performing a neighbor search on the metadata graph, plus accessing multiple images.
3. **Query 3:** retrieve all brain scans corresponding to people over 75 who had a chemotherapy using the drug *Temodar*: Involves performing a more complex metadata graph traversal, plus accessing images corresponding to multiple brain scans.

4.1 Performance Evaluation

As a baseline, we implemented a similar set-up, in terms of functionalities, using off-the-shelf, popular, components: MemSQL Server for metadata storage, Apache HTTP Web server for image storage (comparable in functionalities/interfaces to a cloud blob store), and OpenCV for pre-processing operations (pre-processing is a necessary step before inputing to the CNN). We chose this approach because there are no other systems that integrate all the needed functionalities to provide visual data access together with metadata for this segmentation pipeline. We focus the performance evaluation on the data access, given that it is increasingly becoming a problem on the overall execution time when dealing with analytics pipelines [4].

We use the following configuration (both for VDMS and the baseline): Intel® Xeon® Gold 6140 CPU @ 2.30GHz CPU server runs in a Linux environment, running Ubuntu 16.04, Python 2.7, and gcc 5.4. The same configuration was used for both server and client machines, connected over a 1Gbps link.

Figure 4 shows a sample from the performance evaluation we have done comparing VDMS to the ad-hoc baseline, using the medical imaging queries described above. *metadata* represents the time spent in querying metadata only, *img_retrieval* represents the time spent on image read from disk plus sending over the network, and *pre-processing* represents time spent when resizing the image. In the case of VDMS, pre-processing happens in the server side. We demonstrate how VDMS is able to perform very well for complex queries without hurting the performance of simple queries. VDMS significantly benefits from co-locating pre-processing operations on images before data is transferred to the user-application, something that is enabled by its unified API.

For instance, in the case of Query 3, a complex query that involves graph traversal and transfer of a large number of images, VDMS is more than 2x faster than the baseline. It can be seen that a large part of the performance improvement comes from the fact that certain operations, like resize to downsample an image, reduce the overall amount of data that has to be transmitted between the client and the server. That effect becomes more visible as more images are retrieved. When more images are retrieved, the metadata performance have less effect in the overall execution time, as it was expected.

Besides its performance, it is important to note that setting up VDMS to work directly with the segmentation pipeline is significantly simpler than having to deal with the three systems used for the baseline all together, and we believe that together with the performance results showed, greatly justify its use and adoption in real and critical scenarios.

Figure 4: Performance evaluated using the medical imaging queries

5 Conclusion

We introduced the Visual Data Management System, designed to enable efficient access of visual data. We presented our rich, JSON-based API, designed to simplify visual data access for data scientists and analytics pipelines. We compared the performance of our system to a baseline of a combination of widely available and used systems. Our findings showed that VDMS efficiently deals with complex queries, providing a performance improvement of up to 2x in the examined medical data search use-case. Furthermore, VDMS requires significantly fewer lines of code to execute complex queries in complex visual pipelines. We intend to continue with the evaluation of VDMS performance different use cases, and to identify more opportunities to optimize and simplify the access of visual data for machine learning and analytics applications.

In Memoriam to Scott Hahn, who guided us through this journey.

He will always be in our hearts and memories.

References

[1] P. Baumann, A. Dehmel, P. Furtado, R. Ritsch, and N. Widmann. The multidimensional database system rasdaman. In *Proc. of the 1998 ACM SIGMOD*, SIGMOD '98, pages 575–577. ACM, 1998.

[2] P. G. Brown. Overview of SciDB: Large scale array storage, processing and analysis. In *Proc. of the 2010 ACM SIGMOD*, pages 963–968. ACM, 2010.

[3] Frederick Nat. Lab for Cancer Research. The cancer image archive. `http://www.cancerimagingarchive.net/`.

[4] V. Gupta-Cledat, L. Remis, and C. R. Strong. Addressing the dark side of vision research: Storage. In *9th USENIX Workshop on HotStorage*. USENIX Association, 2017.

[5] IntelPR. Intel and micron produce breakthrough memory technology, 2015.

[6] J. Johnson, M. Douze, and H. Jégou. Billion-scale similarity search with gpus. *CoRR*, abs/1702.08734, 2017.

[7] A. Lamb, M. Fuller, R. Varadarajan, N. Tran, B. Vandiver, L. Doshi, and C. Bear. The vertica analytic database: C-store 7 years later. *Proc. of the VLDB Endowment*, 5(12):1790–1801, 2012.

[8] MemSQL Inc. The real-time data warehouse you can run anywhere. `https://www.memsql.com/`.

[9] M. Muja and D. G. Lowe. Scalable nearest neighbor algorithms for high dimensional data. *IEE Trans. on Pattern Analysis and Machine Intelligence*, 36, 2014.

[10] S. Papadopoulos, K. Datta, S. Madden, and T. Mattson. The tiledb array data storage manager. *Proc. VLDB Endowment*, 10(4):349–360, Nov. 2016.

[11] The Apache Software Foundation. Apache spark: Lightning-fast cluster computing. `https://spark.apache.org/`.

[12] The Apache Software Foundation. What is apache hadoop? `https://hadoop.apache.org/`.