

MULTI-MODAL VIDEO DATA-PIPELINES FOR MACHINE LEARNING WITH MINIMAL HUMAN SUPERVISION

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The real-world is inherently multi-modal at its core. Our tools observe and take snapshots of it, in digital form, such as videos or sounds, however much of it is lost. Similarly for actions and information passing between humans, languages are used as a written form of communication. Traditionally, Machine Learning models have been unimodal (i.e. $rgb \rightarrow semantic$ or $text \rightarrow sentiment_class$). Recent trends go towards bi-modality, where images and text are learned together, however, in order to truly understand the world, we need to integrate all these independent modalities. In this work we try to combine as many visual modalities as we can using little to no human supervision. In order to do this, we use pre-trained experts and procedural combinations between them on top of raw videos using a fully autonomous data-pipeline, which we also open-source. We then make use of PHG-MAE [33], a model specifically designed to leverage multi-modal data. We show that this model which was efficiently distilled into a low-parameter ($\leq 1M$) can have competitive results compared to models of $\sim 300M$ parameters. We deploy this model and analyze the use-case of real-time semantic segmentation from handheld devices or webcams on commodity hardware. Finally, we deploy other off-the-shelf models using the same framework, such as DPT [41] for near real-time depth estimation.

Keywords: multi-modal machine learning, semantic segmentation, depth estimation, real-time processing, real-time inference, commodity hardware

1. Introduction and related work

In the domain of machine learning there are typically three correlated subsystems, namely the data (1), the models and algorithms (2) and the predictions and actions of a model (3), as presented in Figure 1. Generally speaking the field of research has mostly focused on the models side on fixed benchmarks. This makes sense from a practical point of view: one gets to directly compare a novel solution against existing work in a controlled setting, making the contribution less biased and also more convenient, since they can re-use the data acquisition and processing from the prior work. This approach has

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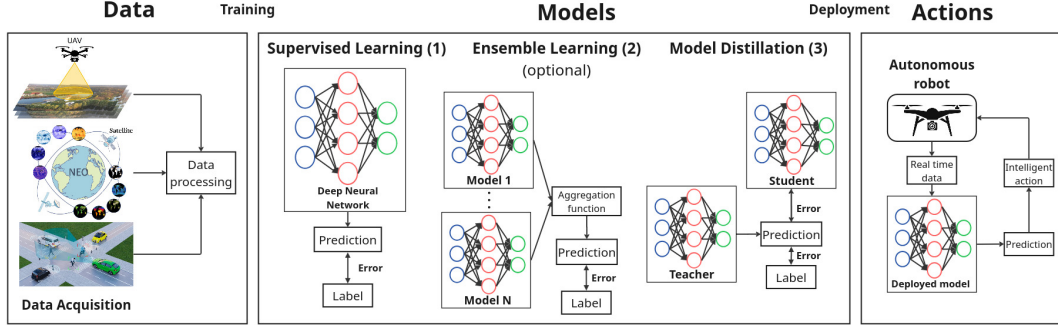


FIGURE 1. High-level overview of an end-to-end machine learning system: from raw data and data processing, to training and optimizing models and lastly by deploying it to interact and control a real hardware autonomously with intelligent actions.

worked very well and has driven the progress of the field with results such as the AlexNet [25] classification network on the ImageNet dataset, the Transformer network [44] on the WMT14 English-German translation dataset [8], DeepLabV3+ semantic segmentation model on the Cityscapes dataset [12], Wav2Vec speech recognition model [5] on the LibriSpeech dataset [35] and many others.

However, there are concerns with this approach. Some argue that we are overfitting on a small set of single or few task benchmarks [40], leading to solutions that don't generalize. Overfitting indices have been proposed [1]. On the other hand, some argue that less mainstream fields, such as atmospheric science, struggle to evolve due to the lack of such benchmarks [15]. A similar issue was identified in the domain of UAVs and aerial image understanding in [30]. In the work of [32], they introduce DronesCapes, a dataset for UAVs on three tasks: semantic segmentation, depth estimation and camera normals estimation, which is also a starting point of this work.

Recently, the trend has been towards massive pre-training with models such as the GPT series for language modeling [39] trained on the WebText dataset (40B tokens), Vision Transformer (ViT) [14] trained on 15M images, CLIP [38] trained on 400M image-text pairs and Segment Anything (SAM) [24] trained on 11M images and 1.1B segmentation masks. In [38], they show that their model is more robust to adversarial examples (ImageNet variants) from the same domain compared to models trained on just ImageNet, showcasing the need for more high-quality large-scale datasets. All the recent improvements have been done by combining the Data and Models 'boxes' from our main figure into a simpler and more scalable loop: creating automatic or semi-automatic datasets with little human intervention, followed by a simple but generic pre-training algorithm and then by a task-specific fine-tuning. In order to do this, one cannot simply rely on existing datasets for training.

For this reason alone, we focus on the *Data (1)* (acquisition and processing) side of things more than is usual, while remaining in the context of Multi-Modal Machine Learning. Multi-modality refers to the use of multiple types of sensors together to achieve some goals or tasks. For example, combining images with depth information or text descriptions provides a richer understanding than using images alone. The world presents information through various modalities, and research aims to leverage these correlated sources. Our data-pipeline extends the DronesCapes dataset [32] from 12K frames for the training set to 80k frames across 3 tasks in an automated fashion from 8 new videos and pre-trained experts only. We create up to 13 new modalities including semantic and depth-derived ones like camera normals or binary segmentation maps, like safe landing areas, buildings, water etc. This dataset is then used to train the PHG-MAE-NR and model [33] as well as the PHG-MAE-Distil variants. These lightweight distillation models (150k or 400k parameters) yield competitive results against models such as Mask2Former [11], that has 217M parameters, which is up to 3 orders of magnitude larger.

Moving over to the Models (2) side, recent trends have been towards large and very large Transformer-based models, with hundreds of millions and billions of parameters. These models, inspired by the domain of NLP [13], use techniques like Masked Auto Encoders (MAE) to do large pre-training on generic and easily acquirable data (like RGB only), followed by task-specific fine-tuning [19] on visual data. Recent works, such as [4], leverage MAE-based solutions for Multi Task Learning (MTL): depth estimation and semantic segmentation. [29] and [34] extend this approach to new modalities, including image, text, audio generation, and action prediction for robotics. These advances are driven by the rise of foundation models pre-trained on massive datasets, enabling zero-shot prediction via prompting and efficient fine-tuning, as seen in [38] and [24]. [6] proposes a multi-modal, promptable model with an instruction-based domain-specific language for generalist capabilities across text, images, audio, and video. Other work on models handling the multi-modality of the data aims to create a graph with neural networks modeling the relationships between modality nodes [45, 26, 17, 32, 36]. One of the main issues with these existing models is that they are designed for performance metrics, not real-time inference. One work that tries to address this limitation is PHG-MAE [33], where they use a MAE-based multi-modal training algorithm that natively incorporates ensembles for performance boosts and consistency across frames. While their main model is also very heavy (with up to 50s per frame), they provide efficient and lightweight distilled models (150 ~ 430k parameters), which enables real-time deployment with little loss in performance.

As we switch to the *Actions (3)* and predictions side, we can observe that it is a much less explored and researched area. Usually this is enabled by the R&D on the models side, followed by a deployment procedure. Once

a model is deployed it is assumed frozen (most of the time) and it becomes more of an engineering problem to run inference and serve predictions reliably without breaking the existing system. This suggests that the neural network is usually used as a module of a larger system, with this hybrid being referred to as Software 2.0 [22], where standard "1.0" procedural code is mixed with neural network predictions to make intelligent actions. One of the main questions and trade-offs is related to where the inference computation happens: on device or on some external server. The first causes the device to have larger compute power, which can increase weight, decrease battery time or increase overall latency. The second solution adds a communication layer between the device and the processing node, which adds variance due to connection issues. Some argue that a distributed system is required to achieve end-to-end real-time performance [7] with specialized nodes doing specialized tasks, like object recognition. Others propose neural architectural changes to reduce the inference duration variance [28] caused by things like object proposals which can be dynamic based on the input image. Nonetheless, solving these latency-performance trade-offs enables intelligent and autonomous devices, like autonomous vehicles [10] or drones for use-cases like flood detection [20], power line failures [3] or search and rescue assistance [2].

In this paper, we study a simpler use-case: deploying distilled real-time models for semantic segmentation and depth estimation. We'll use a consumer GPU on a laptop (NVIDIA RTX 4050 Laptop) for local processing as well as a remote connection to a cloud server (NVIDIA RTX 2080 Ti). We study the case of real-time streaming from a phone camera and analyze the trade-offs of the two setups.

Our main contributions presented in this paper are on the data-processing and automation side as well as model deployment on consumer grade GPUs. Further research on more advanced use-cases, such as autonomous control of a UAV or vehicle enabled by our real-time segmentation model must be studied.

2. Video Representations Extractor data-pipeline for multi-modal machine learning

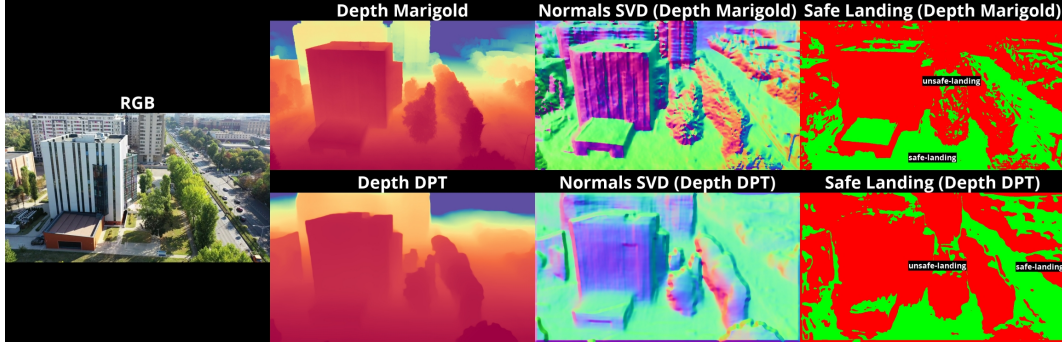


FIGURE 2. VRE showcase. We present six exported representations on top of the RGB frame. The first two are pre-trained experts (DPT [41] and Marigold [23]). Next, we derive two camera normals representations using a SVD-based algorithm [18]. Lastly, we derive safe-landing areas by thresholding the camera normals maps like in the newly introduced DronesCapes2 [33] dataset.

In this section, we’ll discuss our approach for the Data side of Figure 1. In order to streamline the training of multi-modal machine learning models, in the context of videos and scene understanding, we have developed a data-pipeline, named Video Representations Extractor (or VRE for short), which we have also open-sourced at <https://github.com/meehai/video-representations-extractor/>. We discuss architectural decisions as well as how it can be used to create new datasets for other use cases than ours. We also discuss data-pipeline strategies, including multi-gpu batching and real-time streaming. Later, we present a case study based on the DronesCapes [32] dataset for aerial image understanding which was extended in a fully automated way using our data-pipeline: <https://sites.google.com/view/dronesCapes-dataset>. Finally, we discuss PHG-MAE [33], a MAE-based model which has leveraged our data-pipeline by creating an ensemble-based algorithm which operates at intermediate modalities level exported by us. This model was then distilled into a lightweight semantic segmentation model that we can run using the streaming capabilities of the data-pipeline, which we’ll also explore in the Experiments section alongside other models, such as depth estimation [41].

2.1. VRE main loop

Below, in Algorithm 2.1, we can see the main VRE loop. At its core this is all VRE does, but getting this right is not a trivial task.

A VRE process works on a single accelerator (CPU, GPU etc.), a single video (list of frames) and a single representation at a time. By default, it works

Algorithm 2.1 Video Representations Extractor main loop

```

video  $\leftarrow$  [frame1, frame2, ..., frameN]
representations  $\leftarrow$  [RGB, Mask2Former(params), DPT(params), ...]
for repr in topo_sort(representations) do
    batches  $\leftarrow$  make_batches(video, batch_size)  $\triangleright$  batch_size=1 if streaming
    for batch_of_frames in batches do
        if not already_computed(batch_of_frames) then
            out_repr = repr.compute(batch_of_frames, [out_deps])
            img_repr = repr.make_images(out_repr)  $\triangleright$  optional
        end if
        store_on_disk(batch, out_repr, img_repr)  $\triangleright$  only in batch mode
    end for
    store_repr_metadata(batches)  $\triangleright$  stats about this representation
end for
store_run_metadata(video)  $\triangleright$  stats about this video run

```

on batches, where the batch size is defined globally, with the ability to overwrite this option at representation level. For example, we can process many RGB frames at once, however for learned representations (i.e. neural networks), the batch size must be capped by memory requirements, like the (V)RAM capacity of the accelerator. We use the generic term of 'accelerator', but this means CPU (for regular representations) or GPU (for neural representations) in most of the cases, with the ability to generalize to other custom accelerators, such as TPUs, NPUs etc.

The tool does not schedule between multiple videos, but rather the list of frames of a single video are passed as inputs. While this may seem limiting, we present a later how multiple videos and multiple GPUs can be used to scale this simple approach.

Each run on a specific video and list of frames will produce an independent run-level metadata file. This file contains a unique identifier of the run, information about when it started and how long each representation took, as well as information about how many frames were successfully processed or not. It will also produce a raw log file based on the standard output and error for debugging purposes. Moreover, each representation contains a secondary metadata file which offers more granular information at frame-level. It will offer details about how long each frame's computation took, whether it was stored only as binary (npz) or image (png/jpg) or both and so on. For each frame, we also have a unique identifier of the metadata run id, so we can backtrace when each frame was computed. This information is used to know whether this particular frame will be skipped or not on a new run: the *already_computed(batch)* entry in the algorithm above. Note that this representation metadata file is the ground truth, not the actual data on the disk, as this file is faster to process than reading potentially hundreds of gigabytes

of exported files! Modifying the data on the disk may corrupt the metadata and some frames can be wrongly skipped or re-computed on new runs. The metadata file can be manually regenerated from the stored-on-disk data if needed.

2.2. Representation

A representation is the basic block of a VRE run and consists of the definition and computation sides. The definition of a representation is based on a unique name, a set of parameters and a list of dependencies of other representations. This creates a graph of representations, which is topologically sorted to ensure that no cycles exist and that a proper representation scheduling can be obtained. The set of parameters allows us to compute the same representation multiple times with slightly different options. As an example, see Figure 2. Here, we produce two depth maps using two different representations (DPT [41] and Marigold [23]). Then, the camera normals representation (SVD-based) uses the very same algorithm and parameters, but with different depth map dependencies, producing two different outputs. Moving on, the safe-landing representation is similarly built on top of the camera normals representation. We can observe that the safe-landing area produced by the more lightweight DPT depth map misses some details, such as the safe-landing areas on top of the buildings. The computation-side of a representation is simply the code required to run the representation and is defined as simply as $out_repr \leftarrow repr.compute(batch_of_frames, out_deps)$. The code runs at frames level (batched) and it returns the map produced by the representation (i.e. HSV, edges, semantic segmentation, camera normals etc.). The code also receives all the outputs of all the dependencies, which are assumed to have been scheduled for computation before the current representation is run via the topological sort.

Defining the representation. The representations (or experts) that we want to compute are instantiated based on a YAML-based configuration file. In this configuration file we must define the unique name of the representation, its parameters as well as its dependencies (if any). If the dependencies are not properly provided, then $topo_sort(representations)$ will fail with an appropriate error.

The configuration file looks roughly like this (yaml syntax):

```
globals: {batch_size: 10}
representations: {
  rgb: {type: color/rgb, deps: [], params: {}},
  hsv: {type: color/hsv, deps: [rgb], params: {batch_size: 5}}
}
```

2.3. Running strategies: Batching vs. streaming.

One of the dichotomies of data-pipelines is managing the concepts of batching and streaming. The first refers to the principle of scheduling large amounts of data for computation in an offline manner. The main use-case here is reliability and efficiency at scale. On the other hand, there is streaming, where each piece of data must be processed in place with more tolerance to reliability, but less to latency. At its core, VRE supports both modes, see Figure 3.

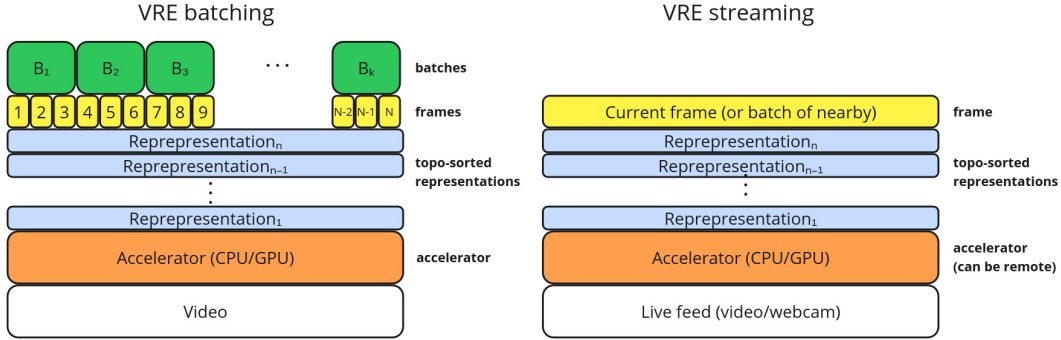


FIGURE 3. VRE processing strategies. Left: the standard batched strategy. We split the frames in batches and then each batch is passed through the algorithm of the representation, followed by a step where the results are stored on the disk. Right: the streaming strategy. In this mode the input is a live video stream (webcam, camera phone etc.) Each frame, or nearby ones (if needed), are processed sequentially by all representations.

Batch mode. This is the default mode for which the tool was created. We use it to schedule entire videos, compute various representations on it (i.e. pre-trained experts or procedural intermediate modalities), followed by storing them for later usage, such as training a new neural network using the exported data. Each expert is processed independently, based on the topological sorting, and the batch size is set such that we maximize the occupancy of the accelerator that does the work (i.e. GPUs). The exported data can be used as-is using the provided ML-ready data reader in python, though the exports are language-agnostic. This mode is aimed at long-running reliable runs and implements various mechanisms, such as retrying with a smaller batch-size in case of OOM errors, a re-entrant mechanism (skipping previously computed frames) and exhaustive diagnostics and log files of each run.

Streaming mode. VRE also supports streaming mode, where the focus is less on reliability and more on fast inference. In this mode, we disable any sort of disk operations (i.e. results are not stored on disk) and optionally, we can disable more features, like creating images from raw predictions, depending on the application at hand. In Figure 4, we provide a basic diagram of how VRE integrates in a larger system, where frames can come from an external source

(i.e. video, webcam, phone camera etc.), can be processed on an external machine (i.e. cloud GPU) and can be used to control an external device (i.e. robot, drone etc.).

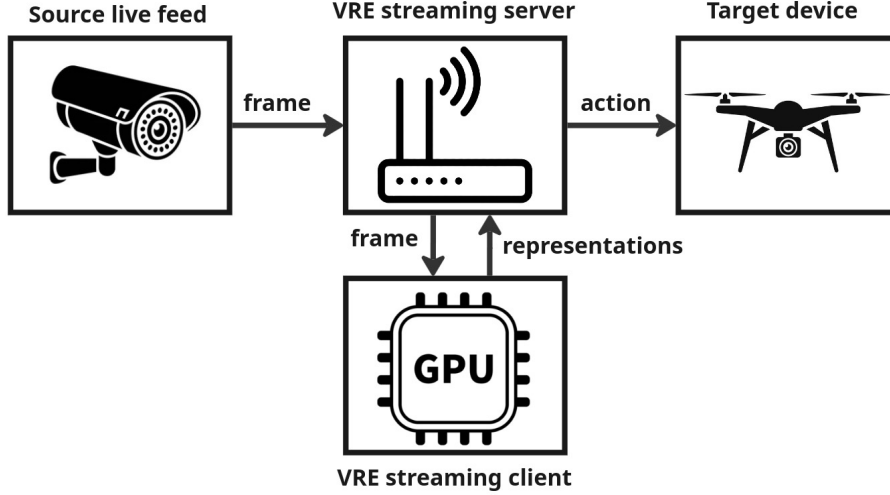


FIGURE 4. VRE streaming architecture. We read frame by frame from the source (i.e. drone camera), process it on the VRE streaming client (i.e. cloud or local GPU), analyze the results and pass the actions to the target (i.e. drone controller). Notably, all these components can live on the same machine but they can also communicate through the network.

We provide various integrations through standard Linux tools (i.e. pipes) which allows VRE to read and write raw frames to standard input and output (or sockets). For example, one can read from the standard input, while the frames come from a webcam and are piped through applications like ffmpeg [43]. Using the same mechanism, we support network streaming, by creating a TCP socket allowing us to run VRE on a cloud server with a powerful GPU while piping the frames in and out of the server via tools like netcat which acts like a (network) pipe. This means that any computer or node that can be accessed by a VRE client (i.e. public IP, ssh tunneling etc.) can be used for computation. The trade-off here is that the network latency can be too prohibitive for the application, especially if one must do real-time processing such as controlling an UAV based on the stream of predictions. It should be noted that ideally we’d use a UDP socket with optimized video encoding for live-streaming for better performance, however, for simplicity, we use a TCP server and raw RGB frames, meaning that there is room for performance optimizations. We provide more concrete examples in the experiments section, where we use a mobile camera for raw frames, and compare a laptop GPU vs. a cloud GPU for real-time and near real-time semantic segmentation and depth estimation inference.

2.4. Multi-GPU batching strategies

In batching mode, if multiple accelerators are available (i.e. nodes with ≥ 1 GPUs), VRE has support for a multi-gpu setup. This, of course, only applies to representations where a GPU is needed in the first place, such as pre-trained neural networks, also called experts in some contexts for semi-supervised learning and distillation. The main requirement for such a representation, internally called a *Learned Representations*, is to properly implement a *setup(device)* method, where the GPU model is moved to the device. In Figure 5, we present two different multi-gpu strategies that can be applied by spawning multiple VRE processes on a single video.

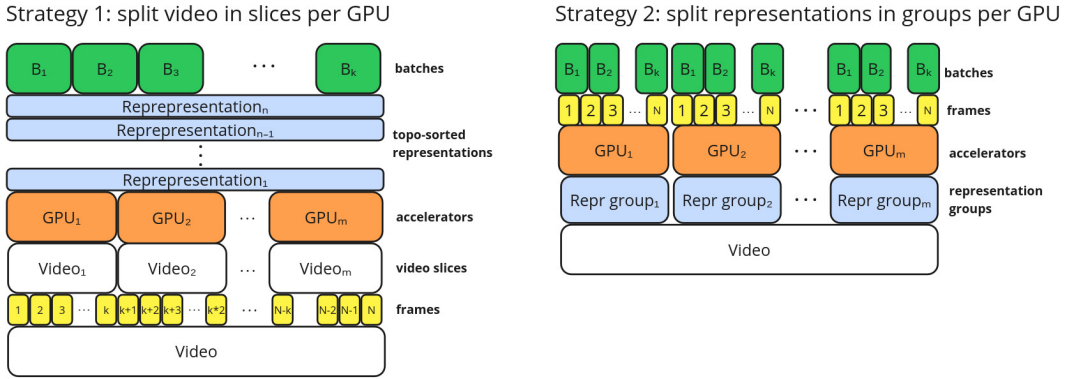


FIGURE 5. VRE multi-gpu batching strategies. Strategy 1: Slice the video in multiple independent chunks. Strategy 2: split the video’s representations in sub-groups.

Strategy 1 is the simplest and most effective one. The video is treated as multiple independent video chunks and assign each to one VRE process and to one accelerator (GPU). This strategy has the advantage that it is consistent (i.e. each GPU will finish at around the same time) and ensures good utilization of each GPU. Furthermore, this strategy also works on distributed environments, allowing us to schedule a video on multiple machines as well, given that we don’t overlap the chunks. The user must then optimize the configuration (i.e. batch size, computation parameters etc.) such that each frame is computed in the optimal time across all representations. The main limitation with this strategy is that all the representations must be computed by the same VRE process. In some scenarios, we may wish that simple independent representations (i.e. RGB, HSV, edges) do not block an entire GPU, especially if they are not dependencies of other complex representations. This is where Strategy 2 comes into play: one video (or video chunk) can be further split into independent representation groups. For example we can have a representation group that computes a depth representation and a camera normals (which depends on depth) representation on one GPU, a secondary group that computes semantic segmentation on another GPU and a third group that

computes HSV and Canny Edges on just a CPU. These can run in parallel on three separate VRE processes, as they are independent from each other. As a recommendation, a user should first start with Strategy 1 and optimize a single configuration for all representations on a single frame, followed by chunking the video based on the number of available accelerators. For most use-cases, one can stop here. Strategy 2 can be then seen as fine-tuning, where the already-optimized configuration is split in multiple sub-configurations to separate GPU representations (i.e. neural networks) from CPU representations (i.e. HSV or Canny Edges).

VRE natively supports this via the `--frames A..B` CLI flag, meaning that one can start 8 VRE processes (one on each GPU) on 8 subsets of the same video, with results stored in the same output directory without any clashes. Furthermore, we have a helper CLI tool, `vre_gpu_parallel`, which can be used to implement Strategy 1.

```
CUDA_VISIBLE_DEVICES=0,1,2,3 vre_gpu_parallel \
  VIDEO -o DIR --config_path CONFIG --frames 0..100
Executing: CUDA_VISIBLE_DEVICES=0 vre VIDEO \
  --frames 0..25 -o DIR --config_path CONFIG
...
Executing: CUDA_VISIBLE_DEVICES=3 vre VIDEO \
  --frames 75..100 -o DIR --config_path CONFIG
```

This tool simply spawns N sub-processes after properly splitting the frames. If the `frames` flag is not provided, it will slice the whole video. Note that any potential race conditions on the same output directory are solved by using atomic write operations, as we explain in the next section.

2.5. Data format

In batching mode, we want to store the data on the disk such that it can be later loaded for various use-cases, such as training a neural network on top of this export. In order to do this, VRE creates a disk-based data structure which can be loaded and analyzed efficiently. The structure on the disk looks like this:

```
video.mp4
video_vre_export/
- .logs/[run_metadata_ID.json, log_ID.txt, ...]
- repr_1/
  - representation_metadata.json
  - npz/[1.npz, ..., N.npz]
- repr_2/
  - representation_metadata.json
  - npz/[1.npz, ..., N.npz]
```

– jpg / [1.jpg , ... , N.jpg]
 ...

The disk-based data structure leverages the rise of fast SSDs, enabling the loading of large batches of data into the RAM for efficient usage. We also implement speculative loading, where we load two or three batches ahead asynchronously, while the current batch is processed, for example doing neural network training or inference. For each VRE run, there is a run metadata, with a unique ID, containing information about the list of frames that were processed. Moreover, in each representation, there is a representation metadata file which contains information about each frame, including a reference to the run metadata ID.

We’ve discussed earlier about the run metadata and the representation metadata, which are the basic mechanisms for introspection and scheduling. At the start of each VRE run, the tool loads all the metadata files to properly schedule only the frames that were not previously computed. This is called re-entrancy, meaning that the tool can continue previously stopped work with the idea that nothing is lost. An important aspect is the fact that each write to the *representation_metadata.json* file is atomic, allowing multiple VRE processes to compute the same representation on different slices of a video, such as the case for the Strategy 1 in a multi-gpu setup (see Figure 2.4).

In case a representation depends on a previously computed representation (i.e. camera normals using SVD requires a pre-computed depth map), then it is more efficient to load the representation from the disk, rather than to recompute it. In some cases it’s not even possible, for example if a neural network representation depends on another neural network representation, as this would require both of them to be loaded at the same time, which can cause out of memory issues or be very slow due to CPU computation. To support this, each representation must implement two functions:

- (1) *representation.memory_to_disk(out_repr, path)*
- (2) *out_repr ← representation.disk_to_memory(path)*.

By default these two representations are identical, but in some cases (for example semantic segmentation), it is more efficient to store the data as argmaxed class indices (uint8), rather than raw predictions (float32), like logits or softmax-probabilities. These are, of course, more advanced nuances and proper action must be taken based on how the data is used. Sometimes it is imperative that the data is stored as-is, other times it’s good enough to truncate it to float32, while others class indices are just as good!

2.6. VRE repository

At the time of writing, the following algorithms and pre-trained experts are implemented and ready to use.

- Color: RGB, HSV
- Edges: Canny [9], DexiNed [37]

- Optical flow: RAFT [42], RIFE [21]
- Depth estimation - DPT [41], Marigold [23]
- Normal maps: SVD (from depth) [18]
- "Soft" segmentation: FastSAM [46], Generalized Boundaries [27], Halftone
- Semantic segmentation - Mask2Former [11], PHG-MAE-Distil [33]

Upon representation instantiation, the weights of these representations (for learned representations only) are downloaded locally from a cloud storage. Implementing a new representation is as simple as implementing a shared interface with a few methods, such as *compute(batch_of_frames, dependencies)* and *make_image(frame, computed_result)*. For *learned representations* (i.e. neural networks), one must also implement two more methods: *load_weights(path)* and *unload_weights()* which are used to load the networks and clear the memory during execution. Moreover, one can implement more fine levers, such as the previously mentioned *disk_to_memory* and *memory_to_disk* functions.

2.7. Case study: Drones2 dataset. A fully-automated dataset built with VRE.

In this section we present a case study: the Drones2 dataset which was generated using VRE. This dataset as well as a step-by-step reproduction process using VRE are publicly available at <https://sites.google.com/view/drones2-dataset>. Table 1 summarizes the size and modalities of the Drones2 dataset followed by the extended variant: the Drones2-M+ dataset, generated using the VRE data-pipeline.

Name	Data Points (GT labels)	I/O Modalities	UAV scenes	Description
Drones2-Semisup1 [32]	12K (233)	5/3	7	Original train set
Drones2-Semisup2 [32]	11K (207)	5/3	7	Original semi supervised set
Drones2-Test [32]	5.6K* (116)	5/3	3	Original test set
Drones2-M+	80K (440)	14/3	15	All new experts and intermediate modalities on 8 new videos plus the original ones

TABLE 1. Drones2 dataset variations and stats. Numbers in parentheses represent the semantic human annotated data. Data points indicates the number of RGB frames.

The original dataset defines three output tasks: semantic segmentation, depth estimation, and camera normals estimation. Semantic segmentation maps are human-annotated, with label propagation [31] used to interpolate missing frames. Depth and camera normals were generated from raw videos and GPS data using a Structure-from-Motion (SfM) tool [16].

The Drones2 extension, named Drones2-M+, builds upon the initial 23K frames from Drones2-Semisup1 and Drones2-Semisup2 by adding 8 new video scenes sourced from the internet, yielding a total of 57K new frames totalling 80K frames. It generates experts and intermediate modalities with no human annotation using the data-pipeline and the new videos

only. We use both the VRE configuration (batched) as well as the distilled model (streaming) in the experiments section.

The VRE configuration contains the following experts and intermediate modalities:

- semantic segmentation (3): Mask2Former on three released checkpoints
- depth estimation (1): Marigold
- camera normals intermediate modality (1): SVD-based algorithm
- binary semantic intermediate modalities (8): *vegetation*, *sky-and-water*, *containing*, *transportation*, *buildings (all types and nearby only)* and *safe-landing (geometric only and geometric + semantic)*

In total, there are four pre-trained experts (3 Mask2Former variants & 1 Marigold) plus nine new intermediate modalities. All the intermediate modalities are implemented as new procedural representations built on top of the existing representations. For example the 'safe-landing (+semantic)' binary segmentation mask is defined as: $(v2 > 0.8) * ((v1 + v3) < 1.2) * (depth \leq 0.9) * safe_class(semantic)$, where $v1$, $v2$, $v3$ are the 3 angles of the camera normals map and *safe_class* is a true/false mapping on top of the underlying Mask2Former semantic segmentation map. The thresholds (representation parameters) can be updated based on experiments.

2.8. Case study: PHG-MAE. A model designed for intermediate modalities exported by VRE.

Using the DronesCapes2 dataset, the work of PHG-MAE [33] has trained a multi-modal multi-task learning model, designed specifically for this kind of data with just 4.4M parameters. In Figure 6, we can see a snippet of how this model works.

It yields competitive results on the DronesCapes-Test dataset against models such as Mask2Former, a 217M parameters model, almost 2 orders of magnitude larger. However, it has one big limitation: it must run the entire data-pipeline for 13 intermediate modalities, including 3 semantic segmentation neural network experts and one depth estimation expert, for each RGB frame. To solve this issue, the authors also provide a set of distilled lightweight neural networks (150k, 450k, 1.1M, 4.4M parameters) with little to no degradation in performance, enabling real-time semantic segmentation. Below, in Table 2, we present a comparison table of these models.

In the experimental section, which follows, we will make use of these distilled variants of the PHG-MAE model to run the data-pipeline in streaming mode for real-time semantic segmentation.

3. Experiments

In this section we'll go over a few experiments that will demonstrate the capabilities of the Video Representations Extractor (VRE) data-pipeline on real-world machine learning workloads. We'll first go over the batched case,

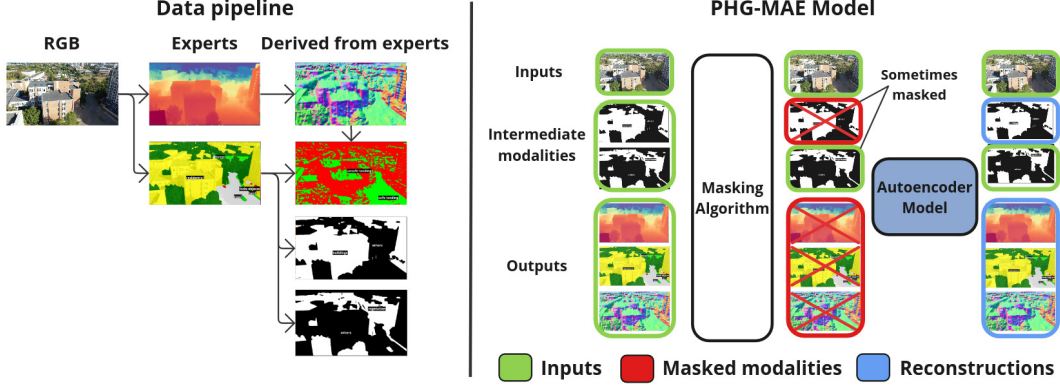


FIGURE 6. The data-pipeline and PHG-MAE model on real data. Left: The process of deriving modalities as pseudo-labels from pre-trained experts using RGB only, followed by deriving new modalities from combinations of experts. Right: integration of all the new modalities in the PHG-MAE semi-supervised training and inference pipeline, with each modality being either input, intermediate or output.

Model	Parameters	Mean IoU $\uparrow$
PHG-MAE-NRand [33]	4.4M	55.06 ± 0.09
PHG-MAE-Distil [33]	4.4M	55.05
PHG-MAE-Distil [33]	430k	54.94
PHG-MAE-Distil [33]	1.1M	54.3
Mask2Former [11]	217M	53.97
PHG-MAE-Distil [33]	150k	53.32
PHG-MAE-1All [33]	4.4M	52.04
PHG-MAE-1Rand [33]	4.4M	51.83 ± 3.3

TABLE 2. Semantic Segmentation performance for the PHG-MAE model, trained on DronesCapes2, a dataset generated using VRE. The -Distil variants, which are trained on top of pseudo-labels generated by the -NRand model.

as introduced in Section 2.3, providing three simple-to-complex experiments. The data-pipeline was initially created for these kinds of workloads: to streamline and standardize the efficient creation of new datasets based on raw videos alone. Then, we’ll go over a more recent addition to the data-pipeline, the real-time streaming component. We provide two experiments with two models: semantic segmentation and depth estimation using pre-trained experts supported out of the box in the VRE repository. We start with a local streaming example, followed by offloading the computation side from a local machine to a remote GPU on an internet-accessible machine.

The command we’ll be using is as simple as:

```
vre VIDEO —config_path CONFIG —o DIR
—frames A..B —batch_size B —skip_computed
```

In the *CONFIG* file we’ll define the representations we want to compute following the yaml syntax defined in Section 2.2. The frames are defined as intervals $[A : B]$, allowing us to skip previously computed frames (if any) in the *DIR*. The batch size is also defined in the config file, and can be defined both globally and fine-tuned at representation level, but for simplicity, we show it in the command line. The output resolution is always the same as the video size. All the batched experiments will be evaluated based on the reported duration in the metadata files of each run. Furthermore, for the streaming experiments, we’ll report the frames per second (FPS). All the experiments are run on a *Intel Xeon Gold 5218 CPU* and one to eight *NVIDIA RTX 2080Ti GPUs*.

3.1. Simple export: RGB and HSV only

We’ll start with a simple experiment computing only the RGB and HSV representations. The RGB one is simply copying the video frame, while the HSV is a basic color transformation, with no accelerator needed. We’ll compare four video resolutions (240p, 540p, 720p, 1080p) for three exports: npz only, npz + jpg images and npz + jpg images + compression. We’ll use the same video and process 100 frames. These experiments should give us an initial hint about how VRE handles large-scale batch processing. The results can be seen in Figure 7.

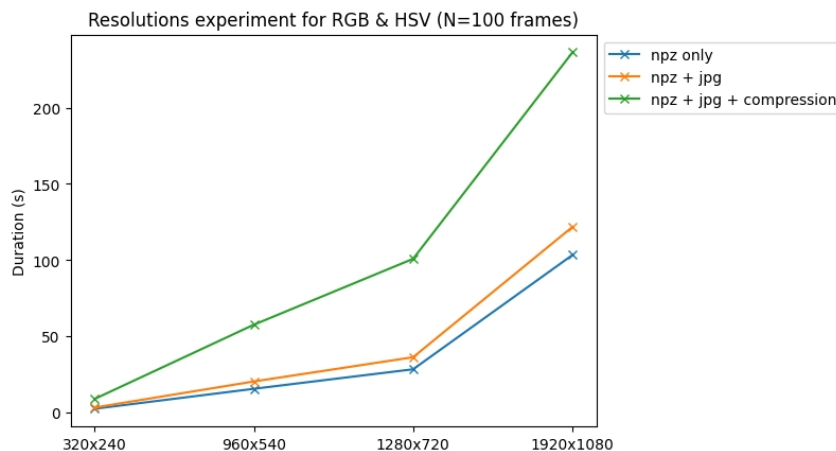


FIGURE 7. Simple export experiment. We compare three output formats for two computed representations: RGB and HSV.

We observe that the duration extends both with a more complex storage (i.e. npz only vs compressed npz), with the frame resolution as well as whether we export only a binary representation or both binary and image (jpg). Interestingly, the compressed export saves about 2.6x disk space (2.4GB vs 907MB on 1080p for the HSV export), while taking only 1.93 times more (236.2s vs 121.8s). This is very useful for large-scale video processing allowing us to make

a space-time trade-off. Notably, since these experiments are on CPU only, the batch size should more or less not matter.

3.2. Batched export: RGB, PHG-MAE-Distil and DPT

In this experiment, we'll try to increase the batch size for two learned representations to observe the performance boost of this feature. The results can be seen in Figure 8.

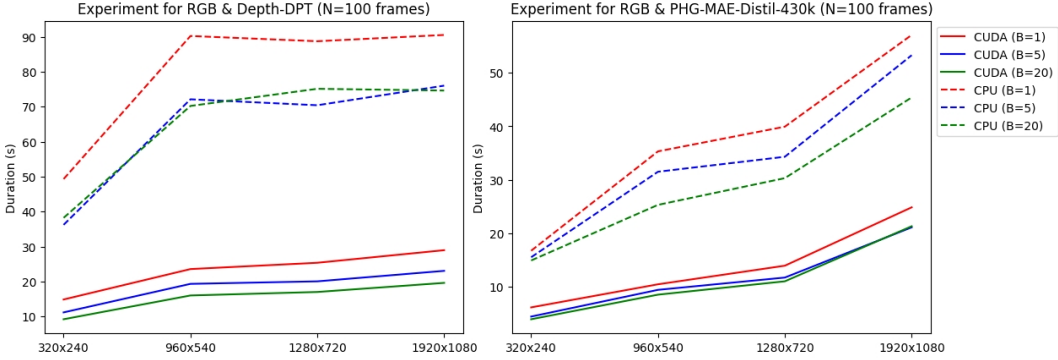


FIGURE 8. Batched export results (CPU vs. GPU) on a local machine with three batch sizes (1, 5, 20) and two models Depth DPT (left) and PHG-MAE-Distil-450k (right).

First, we observe that the GPU (CUDA) variant constantly outperforms the CPU one on each experiment, regardless of batch size. This is expected as machine learning models are optimized for GPU usage. For the DPT model we observe about a 5x improvement, while for the PHG-MAE-Distil model, we see a 2.5-3x improvement depending on batch size. Moreover, we observe a constant improvement as we increase the batch size on both CPU and GPU for all the video resolutions. For the DPT model we see about a 1.5x improvement between the B=1 and B=20. This holds even for the PHG-MAE-Distil model, where we see a 1.1-1.3x speed-up. While these improvements may not be huge, we should always aim at maximizing the usage of our accelerators as each image in batch-mode is independent from each other, allowing for parallel processing. The only reason we should use a lower batch size is due to memory constraints.

3.3. Complex batched export: Drones2 config

Our third and most expensive batched export experiment is obtained by re-using the Drones2 VRE configuration file on a new video (N=100 frames) at the same resolution as the original work: 960x540. In Figure 9, we present a histogram of the average duration of each representation across 100 frames as well as a plot showcasing the scalability of the VRE tool, given more GPUs on a single machine using Strategy 1.

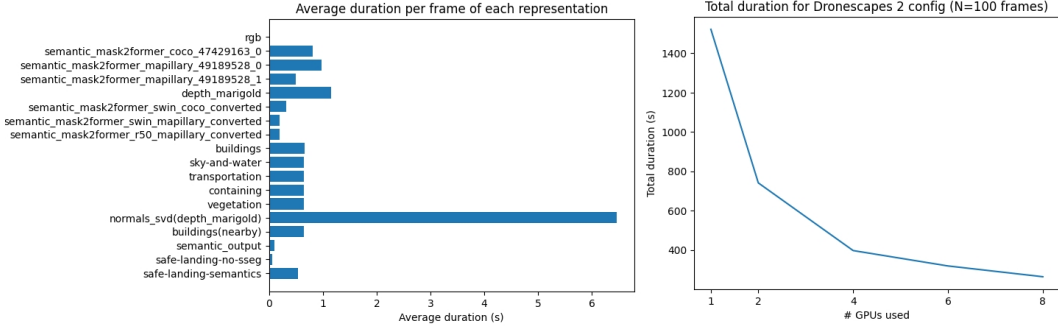


FIGURE 9. Results on running the data-pipeline on the Dronescape2 config. Left: bar plot with the average duration of each representation per frame. Right: total duration for different number of GPUs.

In the left side we provide the statistics of running the experiment on a single GPU. We observe that most of the time is spent on a single representation, namely the normals from SVD algorithm, taking an average of 6 seconds per frame to compute. This makes sense, as this algorithm is not easily parallelizable. On the other hand, even neural network representations, such as Mask2Former or Marigold take about 1 second on average for each frame. On the right side of the figure, we run the same configuration, but using Strategy 1 from Section 2.4 in a multi-gpu setup. We observe that the average time to compute drops almost linearly with the number of GPUs when using 2 or 4 GPUs, but then it plateaus. For 8 GPUs it takes about 264 seconds, a drop from 1521 seconds, while a perfect scaling would mean that the computation would take 190 seconds, thus reaching a 72% scaling efficiency. The most reasonable argument for this sub-linear scaling is the fact that other resources (such as I/O, RAM or CPU) are also bottlenecking the parallelism.

In Figure 10 we provide a qualitative result after running the data-pipeline with the Dronescape2 configuration on a new video.

We observe the 3-level nesting of the VRE process. The experts (neural networks) are derived only from the RGB frame. Then, the first derived intermediate modalities are the camera normals from depth and the semantic segmentation mapping: from the original datasets of Mask2Former to the Dronescape2 set of classes. Then, the final level of derived modalities are built on top of the first two levels of modalities, which are already available at that point due to topological sorting.

3.4. Real-time streaming for machine learning models

In this experiment we will test the streaming capabilities of VRE, following the architecture presented in Figure 4. We'll start with the basic example of doing everything on the same machine: the source is a local video file (960x540 resolution as before), the GPU is on the same machine and the output is just a

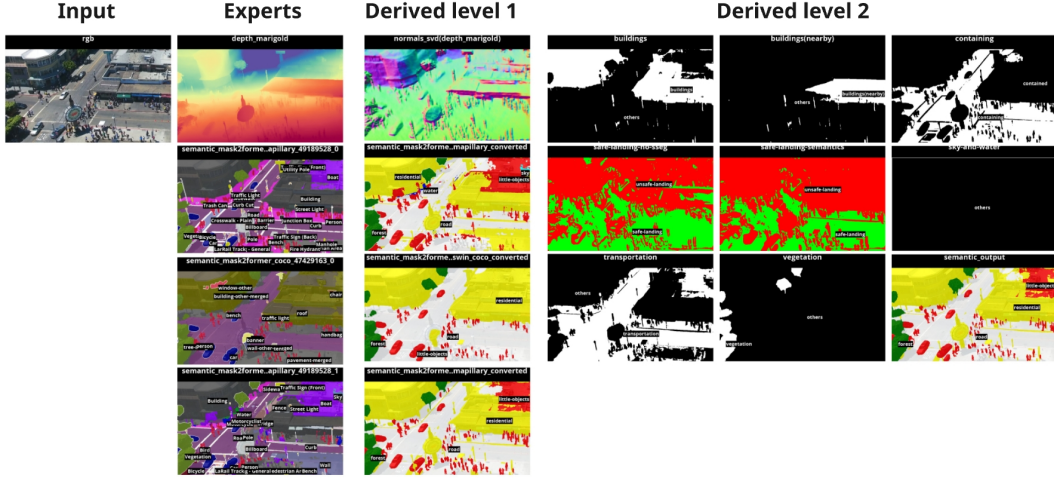


FIGURE 10. All the extracted experts and derived intermediate modalities in the data-pipeline. All are generated starting from the RGB image only.

video player. In Figure 11, we measure the time spent processing in the VRE tool with no model as well as processing through various models: PHG-MAE-Distil (150k~4.4M params), Mask2Former, Depth DPT and Depth Marigold.

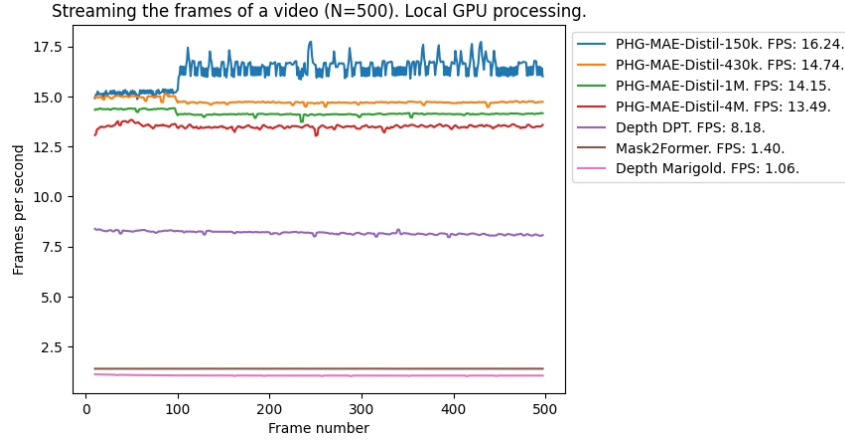


FIGURE 11. Streaming the frames of a video through various ML models. Processed on a local GPU.

We observe that the models have quite low variance, most of the frames take about the same amount of time regardless of the model. Notably, the PHG-MAE-Distil variants can be used for real-time segmentation, while the Depth DPT can be used for real-time depth estimation, which can enable various robotics applications, such as safe navigation through a natural environment. The other two models, while they output more high-quality results, especially Marigold, are better fit for batched export achieving less than 2 FPS.

3.5. Real-time machine-learning streaming with a handheld device and remote processing

In this experiment, we want to offload most of the work of the previous experiment using a handheld device (phone camera) as frames source. Moreover, we want to also offload the processing unit to a cloud GPU compared to using a local laptop GPU to test the trade-offs induced by the network latency. The setup can be seen in the figure below and the FPS results can be seen in Figure 12.

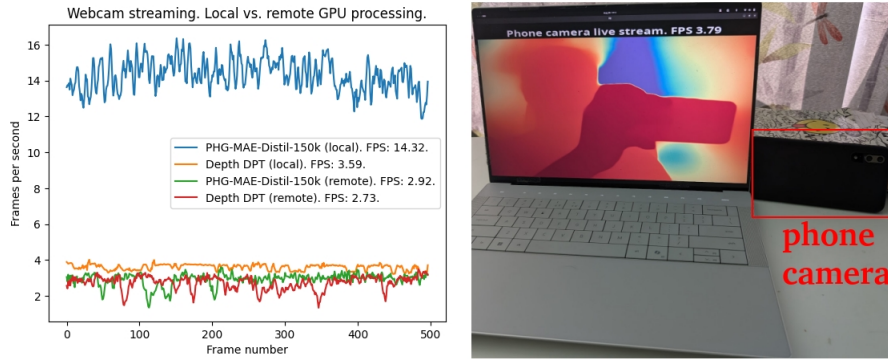


FIGURE 12. Streaming the frames of a phone camera through various ML models. Processed on a local GPU and on a remote GPU. Left: the FPS results. Right: The live-streaming setup.

On the right side we can see the streaming setup: we capture the camera feed from the mobile phone. Then, we relay it to the processing GPU (local or remote). The remote machine is the same as the one used in all the experiments before, while the local machine is the laptop in the image, with a laptop GPU (NVIDIA RTX 4050). Then, the processed images are displayed on the laptop's screen, which is the target. The local processing results are more or less as the ones in the previous experiment, with a slightly lower FPS on average due to the processing being done on a laptop GPU. On the other hand, we observe that both models perform at about 2-3FPS, due to network latencies added. As this is a live feed, we compute the FPS in the following manner: we store on the local machine a CSV file with timestamps based on when the displayed image has changed in pixels. On the remote machine, we only process the Nth frame. In order to do this, we have a thread that reads frames from the network and then the main processing thread (VRE) will get the latest available read frame. Otherwise, due to the fact that the camera works at 30FPS, while the models process only at 2FPS, the queue for unprocessed frames would grow until the server would get out of memory. Furthermore, we only use TCP sockets with raw RGB images, not live-stream specialized video encodings or UDP sockets, which further adds to the latency. Processing live feeds is surprisingly complicated. The main conclusion to be drawn here

is that real-time processing is very hard to achieve over a network, thus local computation should be aimed for if possible.

4. Conclusions

We introduce a machine learning infrastructure data-pipeline aimed at streamlining the creation of multi-modal datasets for training deep neural networks. We present the architectural design and the batched vs. streaming duality, which the tool supports natively. For the batched case, we provide multi-gpu strategies, such as splitting a video in multiple slices or targeting different GPUs with representation groups. We open source the tool alongside a repository of already implemented representations. We then present a case study for how DronesCapes, an aerial image understanding dataset, was created using this tool. Then, we present another case study on how a multi-modal neural network model leverages this dataset to provide competitive results on semantic segmentation with very few parameters. Finally, we provide experiments for both the batched case, as well as a real-time and near-real-time semantic segmentation and depth estimation streaming pipeline using a hand-held phone's camera as live feed.

As future work, our data-pipeline can be improved to support other video streaming native protocols, built on top of UDP, such as RTP. Moreover, the tool works natively on a single node, allowing node-level parallelism, such as multi-gpu setups. However, this approach could be extended to support distributed systems as well, allowing for a more seamless vertical scaling where nodes can be created and deleted on demand. Finally, while we already support a list of existing models on the VRE repository, more pre-trained models could be implemented, such as object recognition, keypoint extraction or video action recognition.

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