Towards Efficient and Accurate Visual Data Analytics System

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Contents

Abbreviations

BN Bayesian Network

CNN Convolutional Neural Network

DL Deep Learning

DNN Deep Neural Network

DoG Difference of Gaussians

DoH Determinant of Hessian

ETL Etract-Transform-Load

FPP Flexiblev Physical Plan

GNN Graph Neural Network

LoG Laplacian of Gaussian

MAB Multi Armed Bandit

ML Machine Learning

MOT Multi-Object Tracking

NN Neural Network

OCR Optical Character Recognition

QO Query Optimization

ReID Re-identification

RNN Recurrent Neural Network

RPS Requests Per Second

SLA Service Level Agreement

SOT Single-Object Tracking

UDF User Defined Function

VAP Visual Analytics Pipeline

VDAS Visual Data Analytics System

VLM Vision Language Model

Abstract

In the context of rapidly expanding digital video data from sources such as surveillance cameras, mobile devices, and social media platforms, traditional manual methods of video analysis are increasingly infeasible due to the sheer volume and complexity of the data. This has led to several research oppurtunity in this field. This research focuses on the development of efficient, scalable,and intelligent video analytics solutions capable of processing large datasets in real-time to deliver accurate, actionable insights. Based on these observations, we define two primary research problems: estimating end-to-end pipeline accuracy without profiling and automating pipeline synthesis using domain ontology. This study contributes to the advancement of video analytics by addressing these challenges and aims to provide a comprehensive framework for developing real-time, scalable solutions.

1 Introduction

In recent years, the field of video analytics has experienced significant advancements, driven by the increasing availability of digital video data and the rapid development of computational techniques. Video analytics involves the automated extraction of meaningful information from video footage, transforming raw video into actionable insights. This technology has far-reaching applications across various domains, including surveillance, healthcare, retail, transportation, and entertainment.

The primary motivation for this research work lies in the exponential growth of video data generated from various sources such as security cameras, mobile devices, and social media platforms. Traditional methods of manual video analysis are no longer feasible due to the sheer volume and complexity of the data. Therefore, there is a pressing need for efficient, scalable, and intelligent video analytics solutions that can process large datasets in real-time and provide accurate, timely information.

In this work; we study various tasks and techniques involved in existing video analytics systems. Broadly we observe the following patterns in the recent works:-

- **Filtering** the data before the application of a more expensive Machine Learning (ML) operation greatly improves latency. This is typically done using proxy models.
- **Indexing**:- Some metadata can be extracted during ingestion time that can later be used at runtime, that also improves the latency.
- **Pipeline Accuracy Estimation**:- Composition of different ML operators produces different accuracy, hence during query optimization we must understand the interaction of these operators with one another in terms of their combined accuracy. This is typically done by profiling.
- **Heterogenous** deployment (edge-cloud) is crucial in realtime usecases, and placement of operators become a focal concern in these cases.
- **Realtime Analytics**:- We also observe a trend towards realtime analytics, rather than ingest now and query later systems. This is mainly due to two reason:- Firstly, due to the progress in modern hardware that allows us to run costly operators on affordable hardware. Secondly, due to large amount of data being generated by countless cameras installed in various settings.

Observations and findings from this study helped us to define following research problems:-

- **Research Problem 1:** Estimating end-to-end accuracy of a pipeline without profiling.
- **Research Problem 2:** Automatic pipeline synthesis based on domain ontology.

The remaining part of this report is organized as follows: In section 2, we provide detailed background on components of a video analytics system, and its use cases. In

section 3, we list down important works that paint the landscape of current state of the art and the journey there to. In section 4, we provide the details of the research problems that we will be working on.

2 Background

In this section, we present background of Visual Data Analytics System (VDAS). We will cover three key areas: 1) the essential characteristics of VDAS, 2) various types of commonly utilized operators in Visual Analytics Pipelines (VAP), and 3) practical use cases of a VDAS.

2.1 Visual Data Analytics System

We characterize a Visual Data Analytics System as a platform that offers several key capabilities to its users. Firstly, it enables users to declaratively construct a Visual Analytics Pipeline (VAP). Secondly, it provides a suite of commonly used operators, reducing the need for users to develop everything from scratch. Third, it includes a runtime environment for executing VAPs efficiently. Optionally, the system can also perform build-time optimization, adapt dynamically during runtime, and offer a distributed runtime environment.

A Visual Data Analytics System can also support real-time analytics, in which video is streaming from a source and analytics is performed and results are available at real-time. With advances, in ML optimized hardware, real-time analytics is possible also desirable.

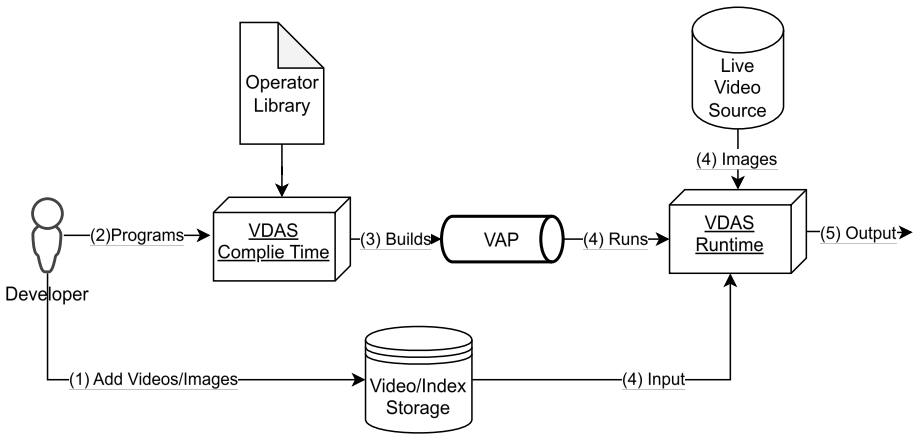


Figure 2.1: VDAS Workflow

2.2 Visual Analytics Pipeline

VAP is logical representation of a visual analytics task. It typically includes multiple visual and non visual operators stitched together in order to reach desirable output. Fig. 2.2 shows an example of a VAP that outputs the timestamp of the frames where a car is found with certain license plate. ML operators are shown in grey boxes.

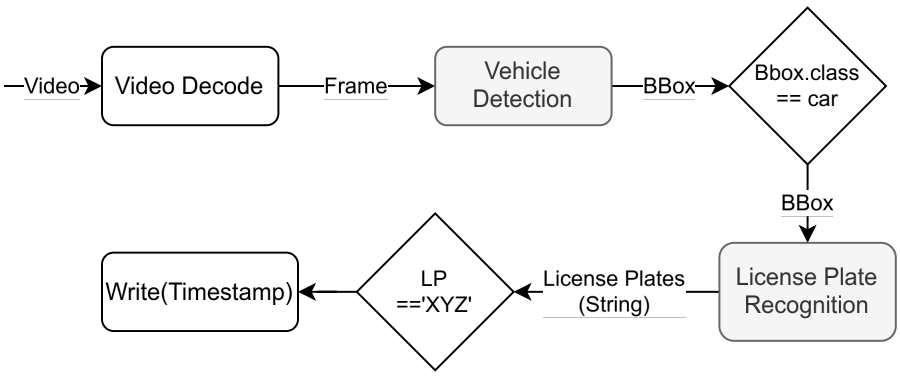


Figure 2.2: Example of a VAP

2.3 Visual Operators

We define a visual operator as an operator that takes one or more images as input, does some processing, and produces some result. We have categorized these operators as video encoder/decoder, classical visual operators and modern ML based operators.

2.3.1 Video Encoding/Decoding

For efficient storage and transmission videos are typically encoded and compressed. Typical encoding process involves:-

- Color Space Conversion:- Video's color space is converted to a more suitable format for compression, often YUV.
- Spatial Compression:- Reduces redundancy within frames using techniques like DCT.
- Temporal Compression:- Exploits redundancies between frames using methods like motion estimation and compensation. In this technique only few of the frames are encoded completely like a static image called *key frames or I-frames*. Other frames in the video are represented by the change since the last frame. These frames are called *delta frames*.
- Entropy Coding:- Further compresses data using algorithms like Huffman coding.

2.3.2 Classical Visual Operators

Low level operators are operations applied directly to raw image data. They typically focus on pixel-level manipulation and involve basic processing tasks that are crucial for extracting primary features and preparing data for higher-level analysis. These operators generally do not involve complex understanding or interpretation of the image content. They are deterministic and involve straightforward mathematical operations and do not require learning. This section provides a non-exhaustive but commonly used low-level operators.

Spatial/Temporal Trimming

Spatial trimming involves cropping the frame of an image or a video to a given dimension. More precisely, let I be an image with width=W and height=H, and (x_1, y_1) and (x_2, y_2) be the top-left and bottom-right coordinate of the rectangular region we want to keep, then

- Original Image: $I(x, y)$ for $x \in [0, W]$ and $y \in [0, H]$
- Cropped Image: $I'(x, y)$ for $x \in [x_1, x_2]$ and $y \in [y_1, y_2]$

- And, $I'(x, y) = I(x, y)$, where $x_1 \leq x \leq x_2$ and $y_1 \leq y \leq y_2$

Temporal trimming involves cutting the duration of a video to specified timestamps. More precisely, Suppose the original video has a total duration T and we want to keep a segment from time t_1 to t_2:

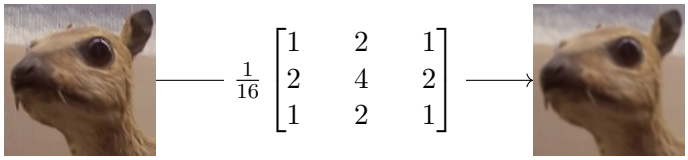
- Original Video: $V(t)$ for $t \in [0, T]$
- Trimmed Video: $V'(t)$ for $t \in [t_1, t_2]$
- And, $V'(t) = V(t)$, where $t_1 \leq t \leq t_2$

Convolution

The general expression of a convolution is:

$$g(x, y) = \omega * f(x, y) = \sum_{i=-a}^{a} \sum_{j=-b}^{b} \omega(i, j) f(x - i, y - j) \tag{2.1}$$

where $g(x, y)$ is the filtered image, $f(x, y)$ is the original image, and ω is the filter kernel. Every element of the filter kernel is considered by $-a \leq i \leq a$ and $-b \leq i \leq b$. Depending on the element values, a kernel can cause a wide range of effects, such as



Original Image Result Image

Figure 2.3: Illustration of a convolution operation.

Affine Transformations

An affine transformation is a linear mapping method that preserves points, straight lines, and planes. In the context of image processing, affine transformations are used to perform a variety of image manipulations, including translation, scaling, rotation, and shearing. Mathematically,

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & t_x \\ c & d & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

where:

- (x, y) are the coordinates of a point in the original image.
- (x', y') are the coordinates of the point after transformation.
- a, b, c, d define the linear transformation (rotation, scaling, and shearing).
- t_x and t_y are the translation components.

Low level feature detection

Edge detection in image processing is a technique used to identify boundaries within an image. These boundaries typically represent significant changes in intensity or color between neighboring pixels. Common algorithms are Canny[6], Sobel[35].

Corner/Interest point detection

Blob detection identifies blobs in an image. A blob is a region in an image where some characteristics are significantly different from the surrounding area. This could include regions of consistent color, texture, or brightness. Blobs can be thought of as objects or features of interest within the image. Common algorithms are Laplacian of Gaussian (LoG), Difference of Gaussians (DoG) and Determinant of Hessian (DoH).

Shape detection involves identifying and classifying shapes within an image. Using this technique we can distinguish shape based on their geometric properties, such as edges, and structural elements. Common technique includes thresholding, hough transform[14], and template matching.

2.3.3 Video Encoding/Decoding

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- Entropy Coding:- Further compresses data using algorithms like Huffman coding.

2.3.4 High Level Operators

High-level visual operators involve more sophisticated and semantically meaningful processing that goes beyond simple pixel manipulations. They focus on interpreting and understanding the visual content, often involving ML to infer higher-level concepts and object relationships in the image.

Image Classification

In image classification, the objective is to categorize an input image into one of several predefined classes or categories. More precisely, let X be the space of images, and Y be the set of possible object classes. A function

$$f : X \to C$$

performs classification task, where $C \in Y$. Common ML models for this task are:- ResNet[41], EfficientNet[36], and BLIP[23].

Object Detection

Object detection involves identifying and locating objects within an image. Unlike image classification, which assigns a single label to an entire image, object detection provides both the classification of objects and their spatial locations through bounding boxes. More precisely, Let X be the space of images, and Y be the set of possible object classes. A function

$$f : X \to (C, B)^n$$

performs object detection task, where n denotes the number of objects present in an image, (c_i, b_i) denotes predicted class label for i_{th} object and $c_i \in Y$, and b_i represents the predicted bounding box coordinates (xmin, ymin, xmax, ymax). Common ML models includes:- YOLO[31], Fast-RCNN[11], SSD[25]

Semantic Segmentation

Semantic Segmentation involves classifying each pixel in an image into a predefined class. Unlike image classification, which assigns a single label to an entire image, and object detection, which localizes objects with bounding boxes, semantic segmentation provides a detailed, pixel-level classification that assigns a class label to every pixel, effectively dividing the image into meaningful segments corresponding to different object categories. More precisely, Given an image X of size $W \times H$, and Y be the set of possible object classes.
A function

$$f : X \to L$$

where $L \in Y^{W \times H}$, can perform semantic segmentation. Common ML models include:- UNet[34], and DeepLab[8].

Instance Segmentation

Instance segmentation involves identifying and segmenting each object instance in an image. Unlike semantic segmentation it not only distinguishes between different object classes but also seperates individual instances of the same class. Each instance is segmented out and assigned a unique identifier. Given an image X of size $H \times W$, and Y be the set of objects present in the image.
A function

$$f : X \to L$$

where $L \in Y^{W \times H}$, can perform instance segmentation task. Common ML models includes:- MaskFRCNN[13].

Pose Detection

Pose detection involves identifying landmarks of the human body(or any other articulated objects) in an image. The goal is to determine the precise position and orientation of these key points to understand the pose and movement of the body. Landmarks are the specific locations on the body such as joints(e.g., elbows, knees) in case of human body. Given an image X be the image and Y be the set of landmarks of an object.
A function

$$f : X \to (A, B, K)^n$$

where n is number of landmarks detected in the image, $k_i \in Y$, and (a_i, b_i) is a pixel in the image. Common technique includes:- OpenPose[7], PoseNet[21], and DeepPose[38].

Object Tracking

Object tracking involves following the movement of objects within a video or across a sequence of images. The goal is to determine the position and trajectory of an object over time, ideally even in presence of occlusion, change in appearance or background clutter. Tracking is of two types:-

- In **Single-Object Tracking (SOT)** a single object is tracked throughout the video, the object of interest is specified by the user

- In **Multi-Object Tracking (MOT)** multiple objects are tracked, depending on the objects being detected by the object detector. This requires us to keep state of every object currently being tracked, as well as add new objects in the state when they are first discovered and remove objects from the state when they are no longer visible.

Re-identification (ReID)

ReID involves recognizing the same entity across different camera views or times. Difference between object tracking and ReID is that the later might need to store larger state than object tracking since the same objects might appear across a large timeframe.

Optical Character Recognition (OCR)

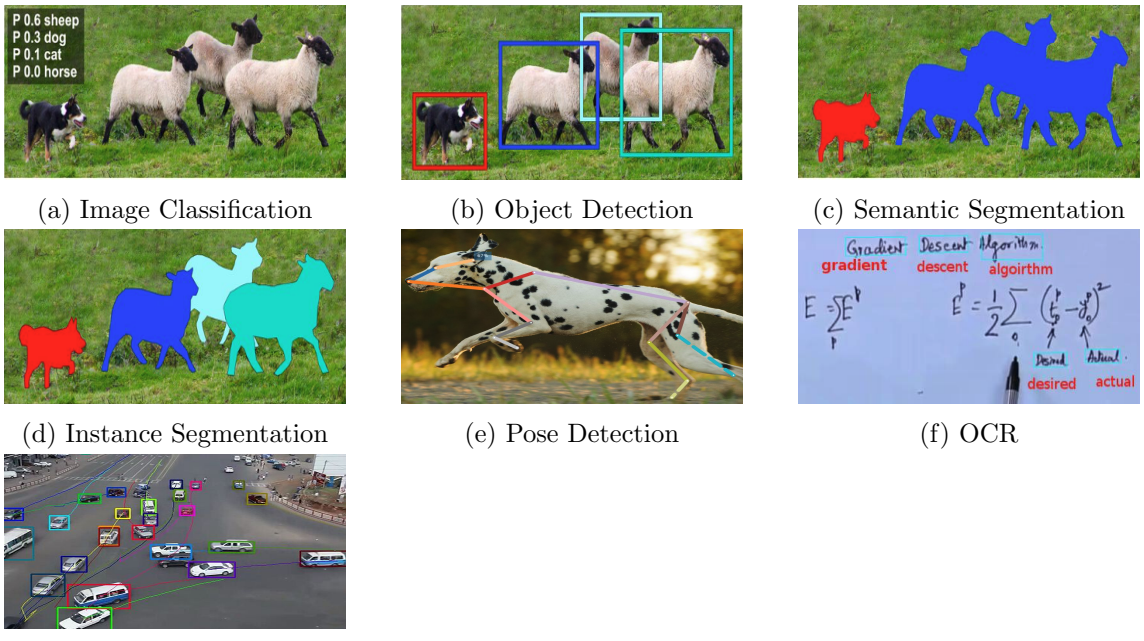
OCR involves converting different types of documents, such as scanned paper documents into editable and searchable data. Primary function of OCR is to recognize text characters in the image. More precisely, given an image X an Y be a set of characters.
A function

$$f : X \to 2^Y$$

where 2^Y is the powerset of Y. Common technique include: Easyocr[24], Tesseract[20], and large multimodal models like Gemini[37] can also be used to extract text from images.

Image Embeddings Extraction

An image embedding is a vector that encodes the semantics of contents of the image. This can be used to compare similarity of two images which is useful when doing image search. These embedding become proxy for the image and cosine distance (or other distance metrics) between them becomes proxy for similarity. Embeddings are usually extracted from a Convolutional Neural Network (CNN)'s penultimate layer. In recent years multimodal (text and images) models such as CLIP[30] are also being used for image embedding extraction. They are trained with a large dataset of pairs of text and image, hence they are able to understand relationship between images and text, allowing image search with a text query.



(a) Image Classification (b) Object Detection (c) Semantic Segmentation

(d) Instance Segmentation (e) Pose Detection (f) OCR

(g) Object Tracking

Figure 2.4: Visual Analytics Operators

2.4 Common Use cases

2.4.1 Traffic Analysis

Increased traffic in urban environments can lead to more accidents and congestion if proper traffic management strategies are not implemented. Intelligent video analysis solutions can be highly effective.

These solutions can be used for following tasks:-

- Automatic traffic violation detection: These systems can identify and record traffic violations such as speeding, running red lights, and illegal turns, thereby improving road safety and enforcing traffic laws.
- Amber alert: Video analysis can assist in issuing Amber Alerts by identifying vehicles or individuals that match descriptions in cases of child abduction or other emergencies.
- Automatic adjustment of traffic light systems: Real-time traffic data can be used to optimize traffic light timings, reducing congestion and improving the flow of vehicles.
- Traffic Statistics: Video systems can collect data on traffic volume, vehicle types, and travel times, which can be used for planning and improving transportation infrastructure.
- Smart parking system: These systems can detect available parking spaces and guide drivers to them, reducing time spent searching for parking and improving overall traffic flow.

2.4.2 Healthcare

- At-home monitoring for elderly: Video systems can monitor patients at home for signs of distress or abnormal behavior, providing valuable data for early intervention and reducing the need for hospital visits.
- Mental healthcare: By analyzing facial expressions and body posture, video systems can help in the assessment of mental health conditions such as depression and anxiety, enabling timely support and treatment.

2.4.3 Retail

In the retail sector, video analysis provides insights into customer behavior and store operations, helping to enhance the shopping experience and improve store performance.

- Determine customer's characteristics: Video systems can analyze customer demographics, allowing retailers to tailor marketing strategies and improve customer service.
- Analyze walking patterns and duration of visit: Understanding how customers move through a store can help optimize store layout and product placement to increase sales. Tracking the time customers spend in different areas of a store also provides insights into their interests and engagement, informing decisions on merchandising and promotion.

2.4.4 Sports Analytics

- Player tracking and performance analysis: We can track player's movement to analyze their position, speed and stamina. We can also calculate performance metric such as distance covered.

- Ball Tracking: Advanced video systems can track the ball's movement during games, providing valuable data for performance analysis, game strategy, and enhancing the viewing experience for fans.
- Fair Play: We can provide assistance to referees by doing real-time foul detection.

2.5 Datasets

Human labelled datasets are required for training and evaluation of accuracy of a ML models. There is a huge amount of dataset available for computer vision task, so to keep the list precise, we only list the datasets that are frequently used in related works Table 2.1.

Name	**Description**	T
ImageNet	Well known object classification dataset with 1000 different classes	C
COCO	Well known object detection dataset with 80 different classes	C
Pascal VOC	Well known object detection dataset with 20 different classes	C
Objects365	Well known object detection dataset with 365 categories and 2M images	C
VisDrone	Contains 288 video clips captured by drone.	C
BDD	Consists of 1100 hours of video from dashboard cameras on motor vehicle	C
UAV	Consists of 2 hours of video from UAV hovering above a traffic junction	C
taipei, night-street, rialto, grand-canal, amsterdam, archie, coral-reef	Commonly used dataset in related works	V
CelebA	large-scale face attributes dataset with more than 200K celebrity images, each with 40 attribute annotation	F
Cable TV News Dataset	The dataset includes near recordings of various TV Channels with caption and person detection	F
CityFlow-NL		

Table 2.1: Visual Datasets

3 Related Work

In this section we will describe the related existing systems in the area of video analytics. This will help us understand the landscape of current video analysis. The works are listed in ascending order of their publication year.

3.1 Video Analytics Systems

3.1.1 Optasia [26]

Optasia was one of the earliest attempt at scaling video analytics. They build on top of Microsoft's SCOPE system, and uses SCOPE's interface and runtime. They recognized that:-

- Different pipelines running simultaneously may have common intermediate output which can be reused.
- Same pipeline might have operators who have common intermediate operation which can be reused. 3.1 shows 3 query pipelines: amber alert, traffic violation and amber alert + traffic violation. As we can see in (c) common operators are deduplicated to minimize the query cost.

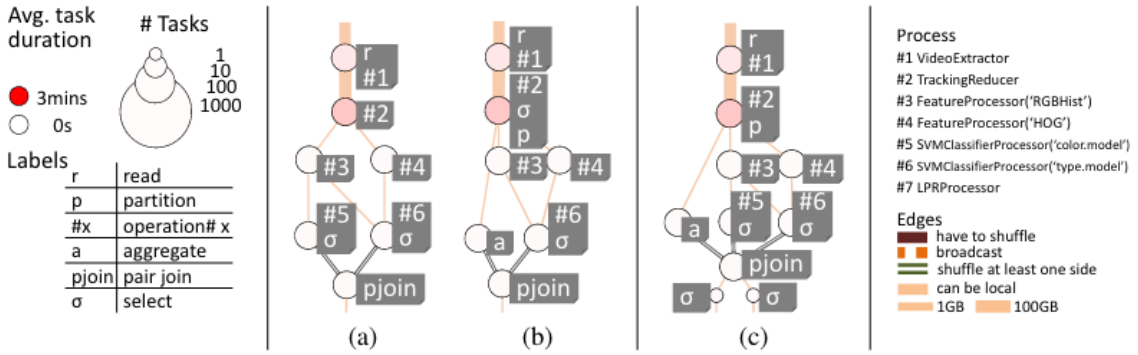


Figure 3.1: Example Optasia Query

3.1.2 NoScope [19]

Researchers observed that is the computational cost associated with applying object detectors to every frame of a video is too high. This process can be particularly resource-intensive and time-consuming. To address this, researchers proposed two innovative approaches:

- Difference Detector

  The first approach involves the development of a difference detector. This detector is designed to identify significant changes between consecutive frames in a video. The core idea is to only invoke the more expensive object detector when a notable

change is detected by the difference detector. This approach significantly reduces the number of frames that require full analysis, thereby saving computational resources. The difference detector is considerably faster and less resource-intensive compared to the full object detector.

- Specialized Models

  The second approach introduces the concept of specialized models. Traditional general-purpose object detectors are typically large and capable of identifying a wide range of objects, such as buses and apples. However, in many real-world scenarios, the requirement is often to detect a much narrower set of objects. For instance, in a traffic monitoring system, the primary interest might be in detecting only vehicles, not fruits or other unrelated objects.

  To optimize for such specific use cases, the researchers proposed training smaller, specialized models tailored to the particular objects of interest. These models can be trained using labels generated by the general-purpose detector, focusing solely on the relevant subset of objects. This leads to models that are more efficient and faster while maintaining accuracy for the targeted detection tasks. These smaller models are trained on the labels produced by the larger model, during the video ingestion time.

They second idea is very important and is refined further by later works. In figure3.2 we see comparison between traditional Deep Neural Network (DNN) inference and optimized inference, at every frame only difference detector is run, which is the fastest operation, if a difference is detected then only a lightweight proxy model is run, if proxy model indicates that bus is present then only the heavier model is run.

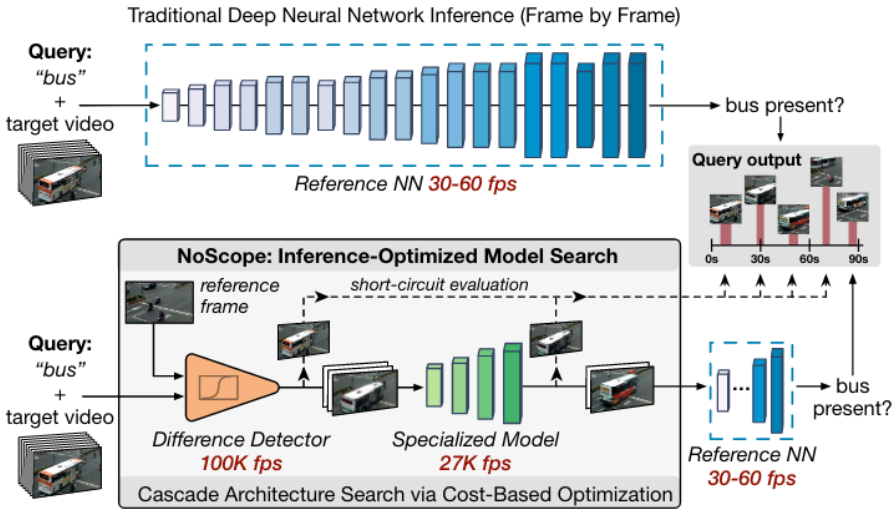


Figure 3.2: NoScope Architecture

3.1.3 VideoStorm [43] (Needs work)

Researchers recognize that there is a tradeoff between accuracy and latency of the pipeline. And they provide the user with an interface to express which parameters of a UDF maybe tuned. In an offline process different value of these parameters are explored to create a profile of the pipeline.

3.1.4 Focus [15]

Researchers criticize NoScope because there can be 'any number of object classes' that could be queried later and running even lightweight binary classifiers for many classes can be expensive. At ingest-time, Focus classifies the detected objects using a cheap CNN, clusters similar objects, and indexes each cluster centroid using the top-K most confident classification results, where K is auto-selected based on the user-specified precision, recall, and cost/latency trade-off point. At query-time, Focus looks up the ingest index for cluster centroids that match the class X requested by the user and classifies them using the GT-CNN Finally, Focus returns all objects from the clusters that are classified as class X to the user.

The idea of indexing at ingest time is also very important and refined in the future works.

In fig3.4 we see that at ingest time top-k index is created, and at query time instead of running a heavy CNN on all the frames, we run it only on the frames whose centroids are classified as class X.

3.1.5 Chameleon [17]

Researchers claim that figuring out a suitable pipeline configuration once before the execution is not enough. The best configuration now may not be the best after a while. For example, we may use a low frame-rate when cars are moving slowly without impacting the accuracy of the vehicle count. In contrast, using the same configuration when traffic is moving fast will hurt the accuracy. They realized that naively doing periodic profiling

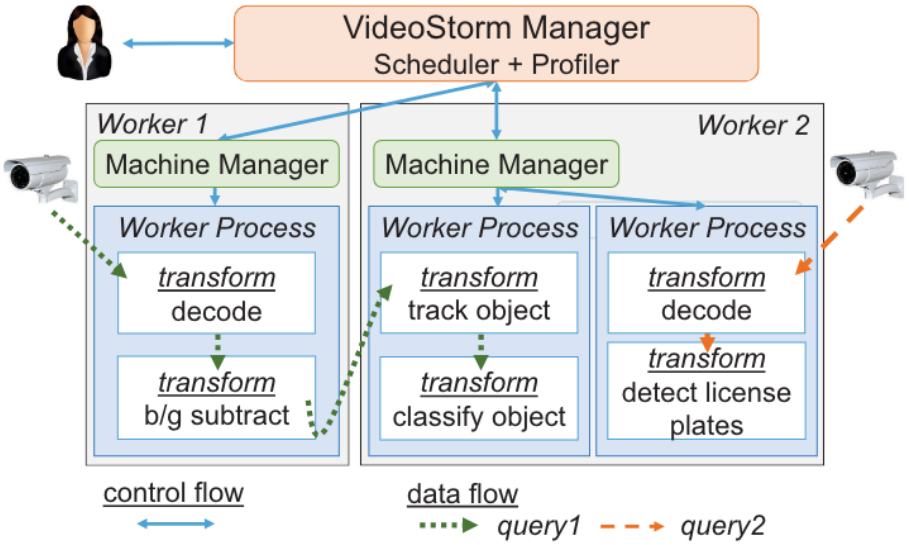


Figure 3.3: VideoStorm Architecture

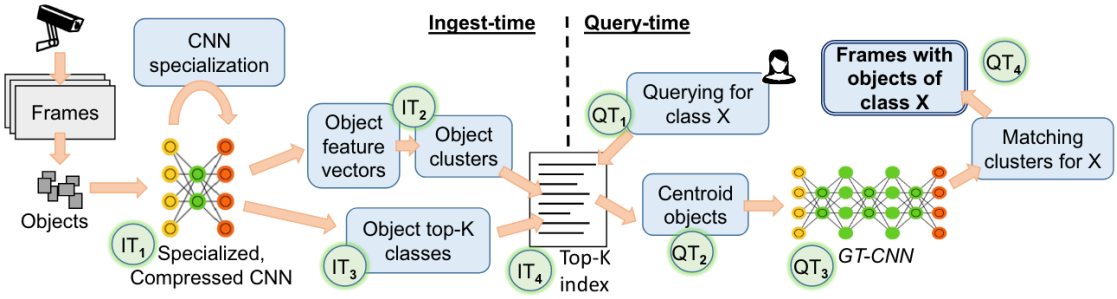


Figure 3.4: Focus Architecture

different configurations is not optimal as there can be exponentially as many. Hence, they exploit the following three properties:-

- **Persistent characteristics over time**:- Good configurations tend to consitently produce good performance. So no need to consider all configurations. Consider only top-k 'good' configurations.
- **Cross-camera similarity**:- Cameras that observe similar scene will have similar optimal configuration. So we can share top-k configurations between them.
- **Independence of configuration knobs**:- Researchers observed that typically individual knobs have independent impact on accuracy. So exploration space reduces to linear from exponential.

Following technique is used to exploit the above-mentioned properties:-

- A "leader" video is profiled at the start of a "profiling window" and a set of good (top-k) configurations is found.
- This set is shared among "follower" videos who are similar to the leader.
- Both the leader and followers then restrict their search to this top-k set when choosing configurations over time, until the start of the next profiling window (when a new top-k set will be obtained from the leader).

Figure3.5 shows how the above technique works in chameleon. The horizontal lines represent video feeds generated by three cameras (one leader, two followers). The solid vertical lines separate the profiling windows. The blue circle represents profiling, and dark blue circle is full profiling which is only done on leader. The red arrow shows the propagation of the top-k configs both temporally (within a camera) and spatially (to other cameras).

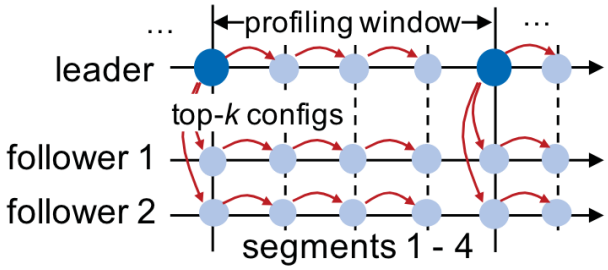


Figure 3.5: Chameleon Technique

3.1.6 DeepLens [22]

Researchers try to create the 'narrow waist' for visual analytics. In that attempt they build an end-to-end system, while charting future works. The abstraction they used is a *Patch*, which contains reference to the image that created it, main data of the patch, and a key-value metadata. Operators work on an iterator of patches and outputs an iterator of patches. The system's overview in figure3.6 is as follows:-

- **Storage Layer** can store images as well as derived data such as bounding boxes. Queries for image fetching also support filtering on channel, timestamp. The videos can be stored as individual frames requiring no decoding, as well as an encoded file. Multiple types of index are supported for efficient retrieval of derived data.

- **Visual Etract-Transform-Load (ETL)**:- At image load time *patch generators* are run that turns the image into a set of patches. This includes whole-image patches, object detection/segmentation and OCR. For future work automatic pipeline synthesis is suggested.
- **Query Processing**:- Select and joins can be performed on the patches. If indexes are available index joins can be performed else nested loop joins will be performed. For future work, a query optimizer is suggested that optimizes accuracy as well GPU/CPU. Researchers recognize following subtleties in QO:-
  - **Balancing CPU vs GPU**: Researchers note that for smaller queries certain tasks on CPU with AVX can outperform the GPU, however GPU scales better, so selecting placement of operator is also very crucial.
  - **Accuracy is not additive or multiplicative**:- Unlike relation databases visual query results are approximate in nature. Cascade of approximate operators can have correlation that are hard to reason with. For example:- Consider a query *Count all distinct pedestrian in a video*. Two approaches are possible to answer this query:- Filter all pedestrians first, then do a matching of all pedestrians to deduplicate. Or match first then filter the pedestrians. The second approach will have higher latency since we didn't filter anything before matching. However, the second approach will have higher recall (In second case if either of two patch is of pedestrian then we consider it a match).

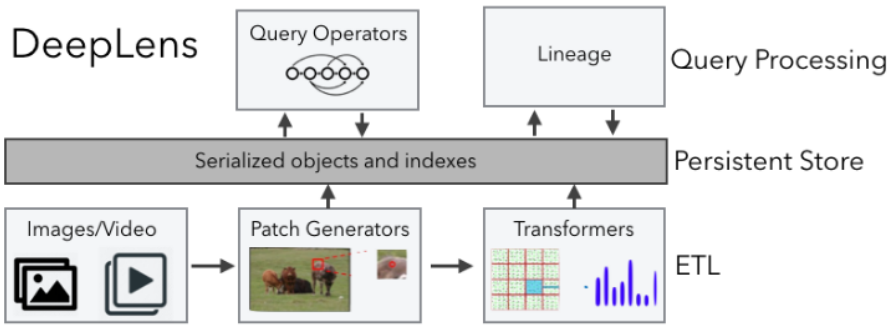


Figure 3.6: DeepLens Architecture

3.1.7 Tahoma [1]

Researchers builds on top of NoScope while criticizing it for concentrating only on computation and ignore the inevitable data-handling costs, such as loading and transformation.

As an example, consider an optimizer choosing between two image classification models ($M1$ and $M2$). $M1$ accepts a 3-channel, full-color, 224×224 image as input while $M2$ accepts a 1-channel, grayscale, 224×224 image. $M1$ has fewer convolutional layers and, despite the larger input, requires fewer tensor operations than $M2$, so its inference is faster. $M2$ uses less rich data than $M1$, but is nonetheless able to obtain comparable accuracy because of its additional convolutional layers. An optimizer that considers only the inference speed would choose $M1$. However, a data system using $M2$ might be faster, as its inputs load in one-third the time of those of $M1$.
Following tasks are performed at ingestion time:-

- train many specialize candidate CNN based binary-classifiers by varying not only CNN hyperparameters but also the input representation. Using this candidate models many classifier cascades are constructed.
- An optimization method evaluates the cascades' accuracy using held-out data.

- Final Pareto-optimal cascades that satisfy the user's application-specific speed and accuracy is identified.

Classification using a cascade is done as following:- The models in the cascade are run in series: image I_i is classified by M_1, and if the output between two given decision thresholds, p_{low} and p_{high}, it is uncertain. So I_i is then classified by M_2. Otherwise, the cascade is stopped and M_1's is accepted. This continues to the final classifier M_n whose output is always accepted. In figure3.7 we see classifier cascade this in action.

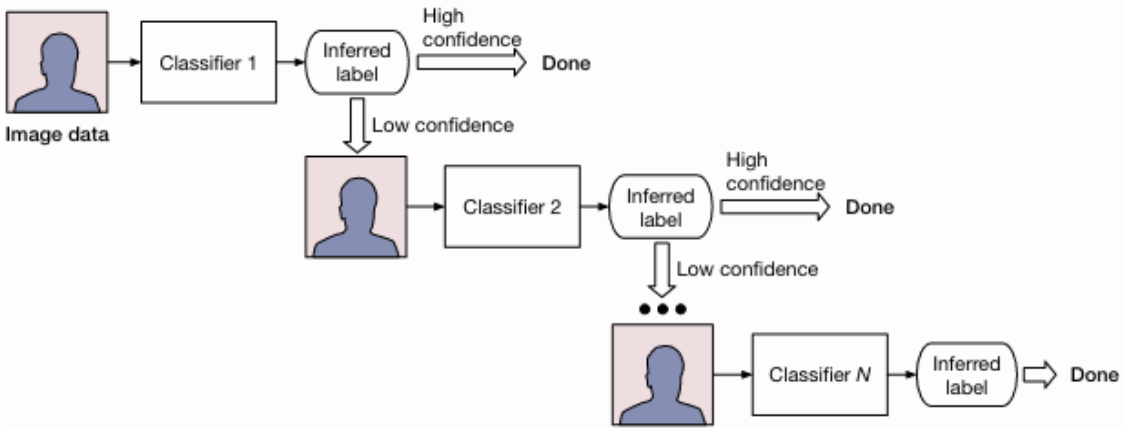


Figure 3.7: Multilevel classifier cascade

3.1.8 BlazeIt [18]

Researchers point out that previous systems (NoScope and Tahoma) do not support aggregation and limit queries. The query interface is extension of SQL (fig3.8) Fundamental idea is to train a proxy model that given an image quickly tells how many object of interest is present in the image.

- **Supporting fast aggregates**:- Researchers train a custom tiny Resnet model to directly answer the aggregate query, i.e how many objects in the image. Object detection models would be slow here since they also give out bounding boxes and labels for those objects, whereas this model only count occurrences. The trained proxy model is applied on all the video frames. To generate labeled data for training the tiny Resnet model, mask r-cnn oracle model is applied on a small subset of frames to derive the answer for the aggregate query (e.g., number of cars).
- **Supporting fast limit query**:- Limit queries are helpful for rare events. We could perform object detection on every frame to search for the events, but if the events are infrequent, random sampling or sequential scans can be very slow. Key intuition is to bias the search towards region of the video that likely contain the event. For this BlazeIt uses the same model trained for aggregates. The frames are sorted by count and confidence given by the specialized NN. The full object detector is then applied until the requested number of objects are found.

3.1.9 Panorama [45]

Researchers tackle the problem of 'unbounded vocabulary'. The object recognition CNNs only handle a finite vocabulary of known targets. This is the direct consequence of their training dataset. For example, Pascal VOC has only 20 classes. So models trained on it can only tell apart these 20 classes. But a real-world query might include a class that the model is not trained on. In such cases, the researchers provide a solution with three main components:-

- **Unified CNN architecture PanoramaNet**:-
  - *Multitask learning*:- Same model does object detection, recognition as well as verification.
  - *Out of vocabulary recognition*:- is done by doing KNN search using the embedding of known objects and query object.
  - *Enabling cost and accuracy tradeoff*:- The lowest layers of the CNNs act as a shared feature extractor for all blocks. All output layers have the same semantics, but they offer different accuracy-runtime tradeoffs. By short-circuiting at an earlier block, the inference cost goes down.
- **Automated offline training**:- A user-given reference model is run on a portion of video to create training data for the training of PanoramaNet.
- **Online inference with short-circuiting**:- The network is made up of several blocks. Inclusion/Exclusion of blocks create an effect of many CNNs chained together, that allows short-circuiting as in Tahoma. A score is computed for a given query at each block and compared it against a pre-computed 'cascade interval'. If the query's score at a block falls in it cascade interval then the subsequent blocks is invoked otherwise short-circuit happens.

3.1.10 Miris [4]

This work focuses on object tracking which involves multiple frames of a video, as opposed to previous works which only focused on per-frame predicates. Researchers claim that proxy model idea does not work here because, when tracking an object, that object will appear on every frame for a while, and the proxy model will not filter any of the frames and as a result expensive object detectors will be applied on every frame. Researchers propose that by controlling the frame rate at which the video is sampled, they can accelerate query execution. If objects can be tracked accurately at say 1 fps

```
SELECT FCOUNT(*)
FROM taipei
WHERE class = 'car'
ERROR WITHIN 0.1
AT CONFIDENCE 95%
```

```
SELECT timestamp
FROM taipei
GROUP BY timestamp
HAVING SUM(class='bus')>=1
   AND SUM(class='car')>=5
LIMIT 10 GAP 300
```

Figure 3.8: Aggregate and Limit Query in Blazeit

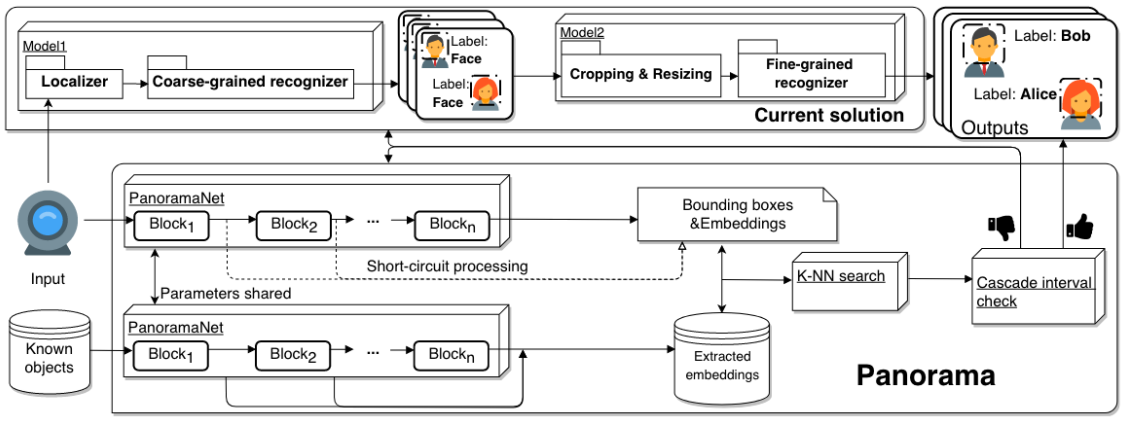


Figure 3.9: Panorama Architecture

instead of 25 fps then the cost can be substantially reduced. Following technique is used for the optimization.

- Object detection and tracking is performed on the video at reduced frame rate to obtain object tracks. Due to the low sampling frame rate, some tracks will contain uncertainty where the tracking algorithm is not confident that it has correctly associated a sequence of detections.
- To increase confidence we can sample additional frames in the uncertain tracks.
- However, if we are certain that the uncertain tracks do not satisfy the predicates anyway we do not need to do additional sampling. This is the key idea.

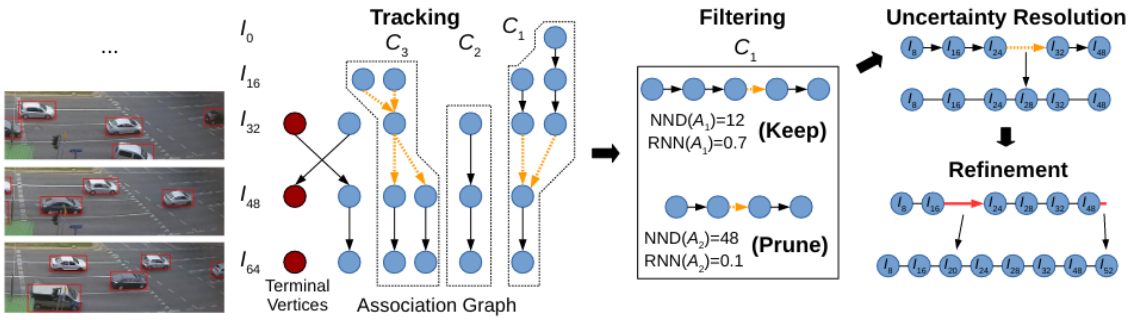


Figure 3.10: Miris Architecture

3.1.11 DiStream

Researchers distribute the Deep Learning (DL) based workload between smart camera and a centralized cluster.
Typical data flow in the system:-

- The frame to be processed is appended in a local queue inside the camera.
- The frame can be processed either processed locally or offloaded to other camera decided by *cross-camera workload balancer*.
- Only some part of processing is done on camera rest is offloaded to cluster. The partition is determined by a DAG *partitioner*.

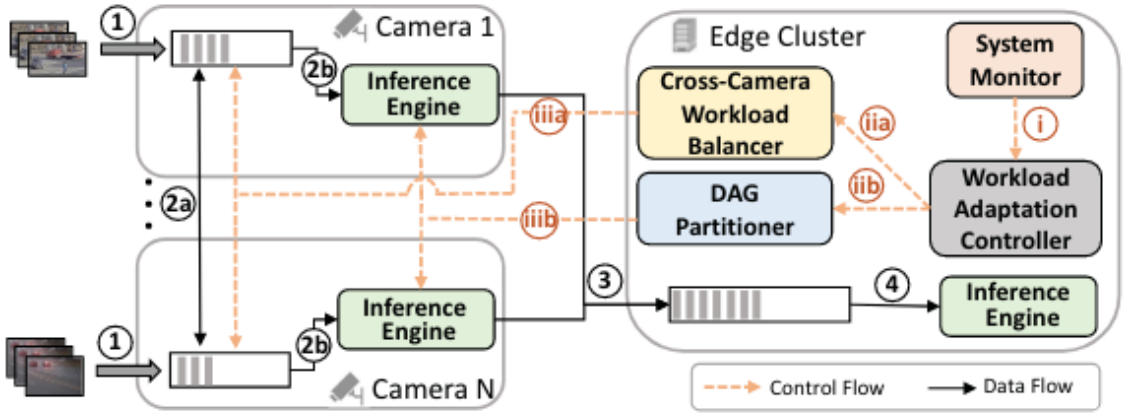


Figure 3.11: DiStream Architecture

3.1.12 JellyBean [39]

Researcher build a system that given resources availability, required latency and target accuracy optimizes the serving cost by selecting appropriate ML models and worker assignment (edge-cloud).
Overall schematics of the system is as follows:-

- **Input** to the system is a logical plan graph G, for each ML operator a list of candidate models with their accuracy profile, required accuracy, and infrastructure specification that contains set of each type of workers each tier has, cost of each type of worker, and the communication cost between different tiers.
- **Accuracy Profiling** of a model is done by varying parent model and seeing the resulting accuracy. For e.g. consider a model with two inputs this model can have the following accuracy profile: (60%,50%) $\rightarrow$ 55%, (50%,60%) $\rightarrow$ 60%, and (70%,90%) $\rightarrow$ 65%.
- **Model Selection**: The graph is traversed in reverse topological order, and assign the model for each node. Each candidate will have an accuracy requirement from the parent operators, these requirements are propagated to the parents and parents are chosen accordingly. After this each node might have multiple candidates, candidate with the lowest cost chosen.
- **Worker Assignment**: The graph can be partitioned once between edge and cloud, and appropriate partition needs to be chosen. Researchers provide a greedy algorithm that assigns workers to each partition.

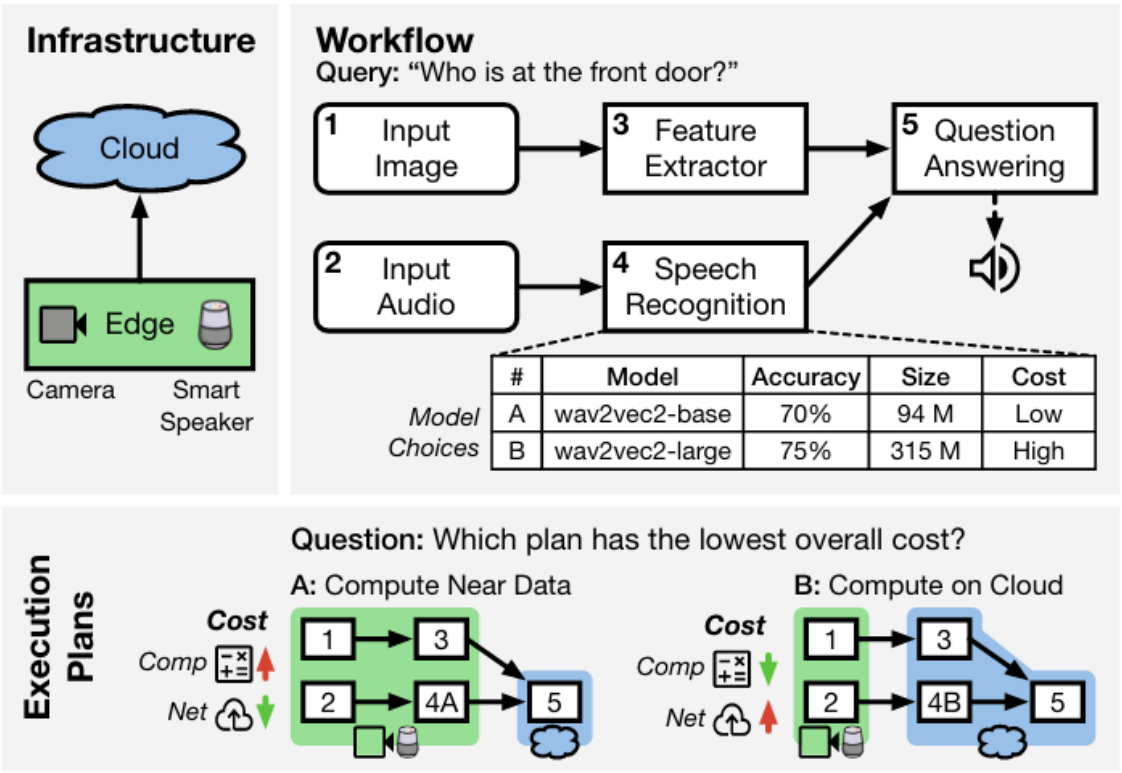


Figure 3.12: JellyBean Architecture

3.1.13 Otif [3]

This work focuses on object tracking queries. In this system all the tracks are extracted from the video during ingestion time. At query time, there is no need to perform video

analytics, metadata extracted during the ingestion time is enough to answer the query. Hence, making it much faster than any system that does query time processing.

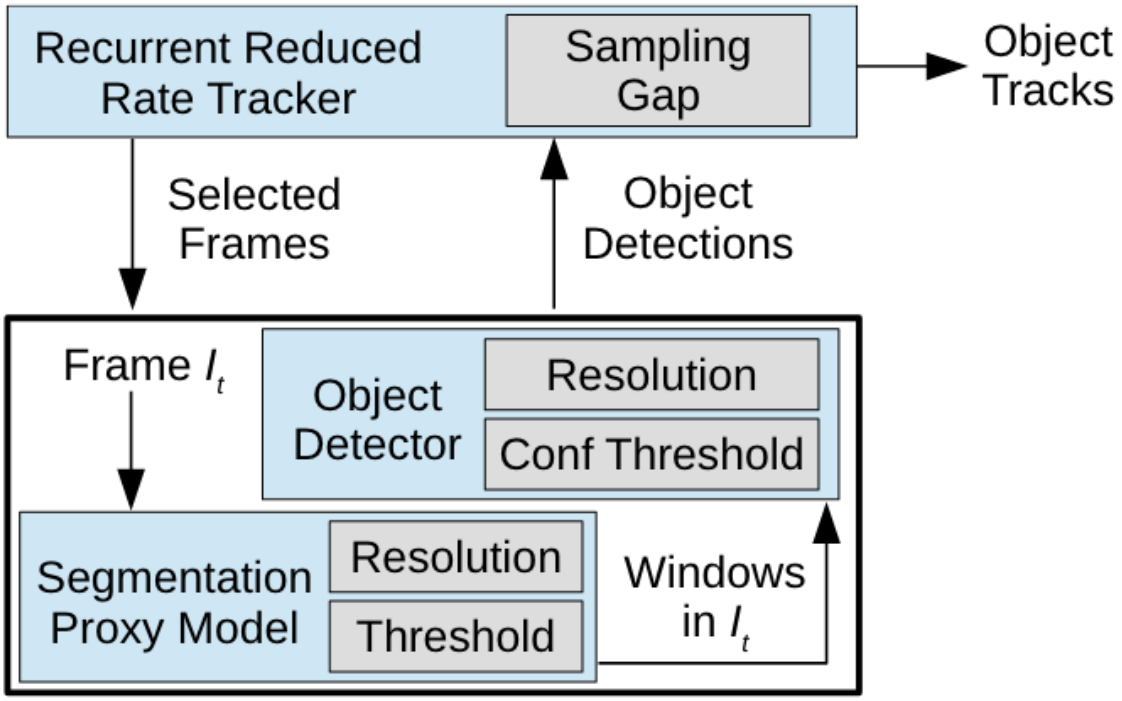


Figure 3.13: Otif Architecture

Following optimizations are also performed during ingestion to make the preprocessing fast as well:-

- **Segmentation proxy model** identifies the regions of frames that contain no objects, and skip object detection processing on these regions.
- **Recurrent reduced-rate tracker**:- Instead of using a Graph Neural Network (GNN) as in Miris, a Recurrent Neural Network (RNN) architecture is used which faster, and is more accurate at low sampling rate.
- **Joint parameter tuning**. There are 5 parameters that can affect the accuracy and latency of the query. They are:- (i) Resolution and (ii) Threshold in segmentation proxy model, (iii) Resolution and (iv) Confidence threshold in object detector, and (v) sampling gap in the tracker. The multiple Pareto-optimal configuration of these 5 parameters are calculated by profiling on a validation set. They will have different accuracy speed tradeoff, user can select one of the configuration.

3.1.14 Viva [32]

Researchers develop an end-to-end interactive video analytics platform, which includes a (i) video file manager, (ii) execution engine, (iii) query optimizer and (iv) embedding cache.
Notable contributions:-

- **Relational hints**, that allows users to express relationships between columns that are difficult to automatically infer, for e.g., mentions of a person in a transcript can be used as a proxy for the person appearing in the video.

- **Multiple Supported Queries**:- Prior works focus on single query type, whereas VIVA supports different types of queries which includes:- *selection*, *aggregation*, *limit*, *similarity* and *joins*.

3.1.15 Seiden [2]

Researchers found that difference between speed of oracle and proxy model is not significant enough for the trade-off in accuracy. Instead, they come up with an alternative plan to generate more accurate proxy labels faster than proxy models. Following is the process:-

- Index Construction (At ingest time):- Label is extracted from each I-Frame video of the video using the oracle model. I-frames can be decoded independently, and I-frames are created by the codec when there is drastic change in the scene, and they tend to be evenly distributed.
- Multi Armed Bandit (MAB) sampler (At query time):- Using MAB sampler more frames between the I-frames are sampled and labelled, for the query to get better estimate.
- Label propagation (At query time):- Proxy labels of the unlabeled frame is propagated from the closest orcale labeled frames.

Using the proxy labels, we can answer the aggregate queries fast, without having to compute labels for all the frames.

3.1.16 Zelda [33]

This work leverages Vision Language Model (VLM) that allows following advantage:-

- Natural language interface:- Other systems use SQL like interface that has limited predicate expressivity compared to natural language.
- Single general purpose model:- Other systems can only use predicates whose corresponding models are available. By using a single large model we can do arbitrary querying.
- Reduced system complexity:- Using a single model reduces model management overhead.

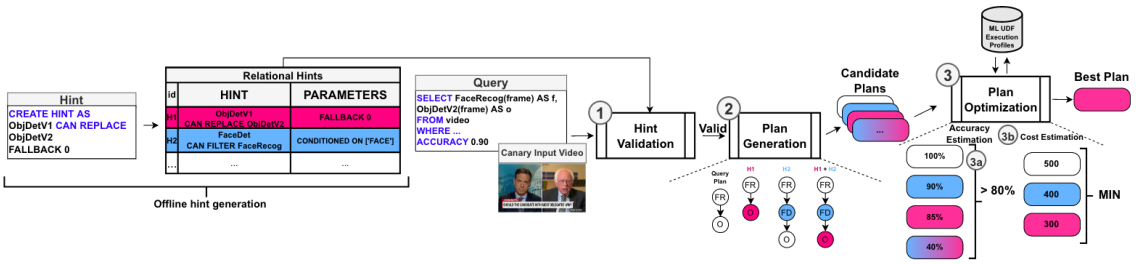


Figure 3.14: Viva Architecture

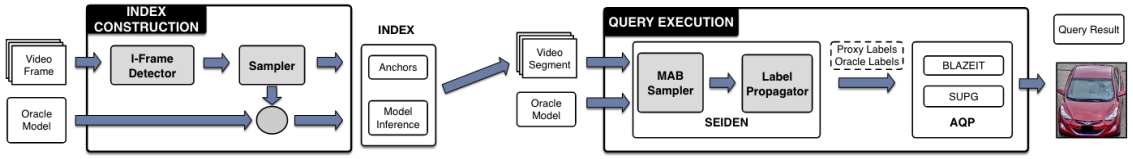


Figure 3.15: Seiden Architecture

To answer a query following steps are taken:-

- Both image frames and input query is passed to the VLM, and using cosine similarity few candidate frames are chosen.
- Apply 'diversify' filters that remove almost similar frames and, quality filter that removes blurry, grainy frames.
- Finally, sort by similarity and show top-K.

3.1.17 VQPy [40]

Researchers develop an object-oriented unified interface for visual queries. Researchers argue that SQL based interface is not ideal for handling object based video queries. Major contribution includes:-

- A video-object-oriented data model: Python is used by users to create 'Visual Object' and 'Visual Queries'. VObj is any object of interest that needs to be extracted from the video, e.g. cars, person. They can have stateless and stateful properties. Visual queries are of three types:-
  - *Spatial Query*:- To express constraint between two objects in the same frame, e.g. distance between person and car in a frame.
  - *Duration Query*:- To express some event occurring over time, e.g. a person loitering from more than 20 mins.
  - *Temporal Query*:- To express some related event that occurs across different frames, e.g. a car hitting a person and speeding away.
- An extensible optimization framework:- The optimization framework can be used to express the optimizations developed in previous works, such as filtering using proxy models.

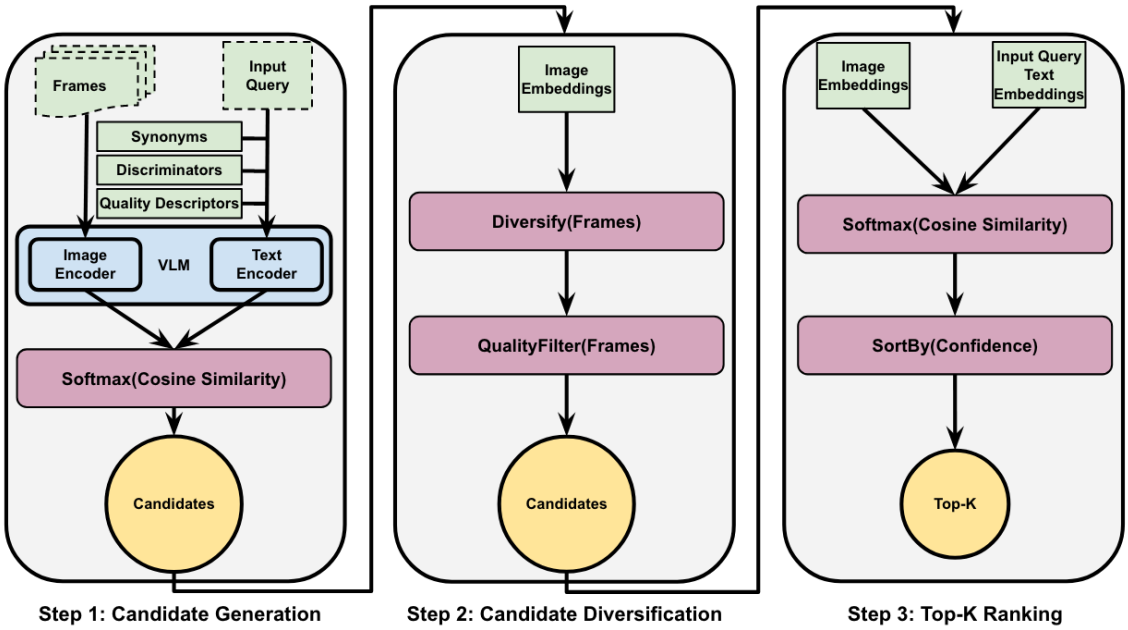


Figure 3.16: Zelda Architecture

3.1.18 Ipa [10]

Researchers perform multi objective (accuracy and latency) pipeline optimization. The user can specify the desired latency, and system will come up with an optimal plan that matches the latency requirement while providing the best accuracy possible with the required latency. Main contribution includes:-

- Pipeline accuracy estimation:- Since exact accuracy of a pipeline is not required and any estimate that preserves the order is sufficient, researchers simply multiply the individual accuracy of the models involved in the pipeline, to arrive at pipeline accuracy estimate.
- Profiler:- profiles the latency of different models for different batch sizes while varying Requests Per Second (RPS). They find that increasing the memory after a certain value (depending on model size and batch size), does not affect latency. So they focus only on CPU cores.
- Optimization Formulation:- Researchers use Integer Programming to formulate the optimization target, and Gurobi solver to solve the IP problem.

3.1.19 Vulcan [44]

Researchers are trying to solve following 4 problems:

- **Constructing the pipeline** All pipelines are constructed based on a template given as:- *InputData -¿ Filters -¿ ML Models -¿ Specialized Task -¿ Result.* Pipeline construction invloves selecting appropriate operators at each nodes.
- **Configuring the pipeline**:- After operators are selected, now we have to select *configuration knobs* in each operator. The configuration must satisfy the accuracy and latency requirement given by the user. This is done using Bayesian Optimization.
- **Online Adaption**:- Vulcan monitors utility (i.e, latency, accuracy, outputsize, bandwidth) change, to detect runtime dynamics (i.e, content, network). To obtain real-time ground truth on query accuracy given unlabelled live data, a dedicated pipeline with the most expensive configuration is launched in the cloud.

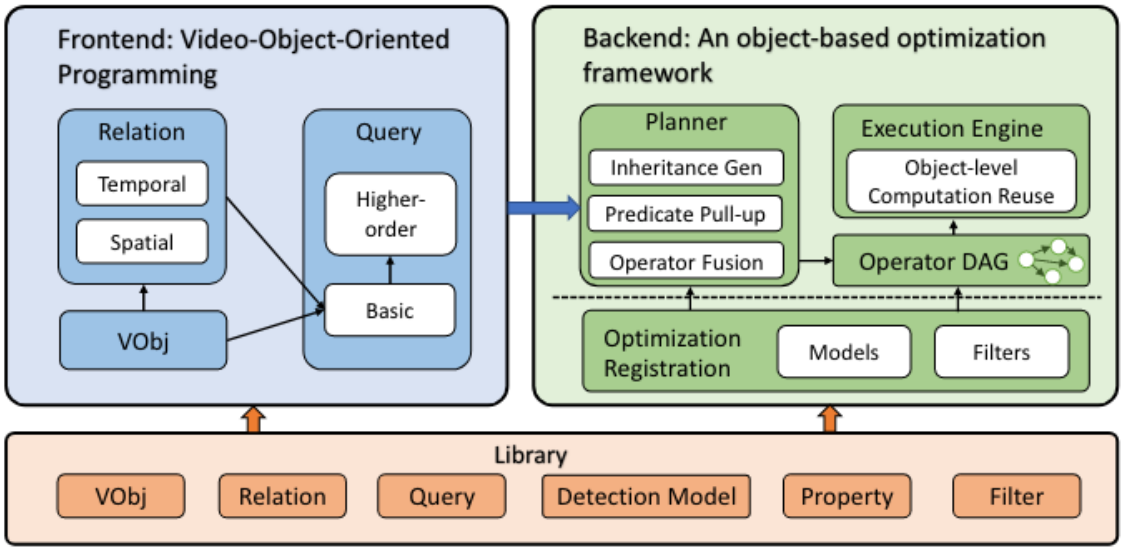


Figure 3.17: VqPy Architecture

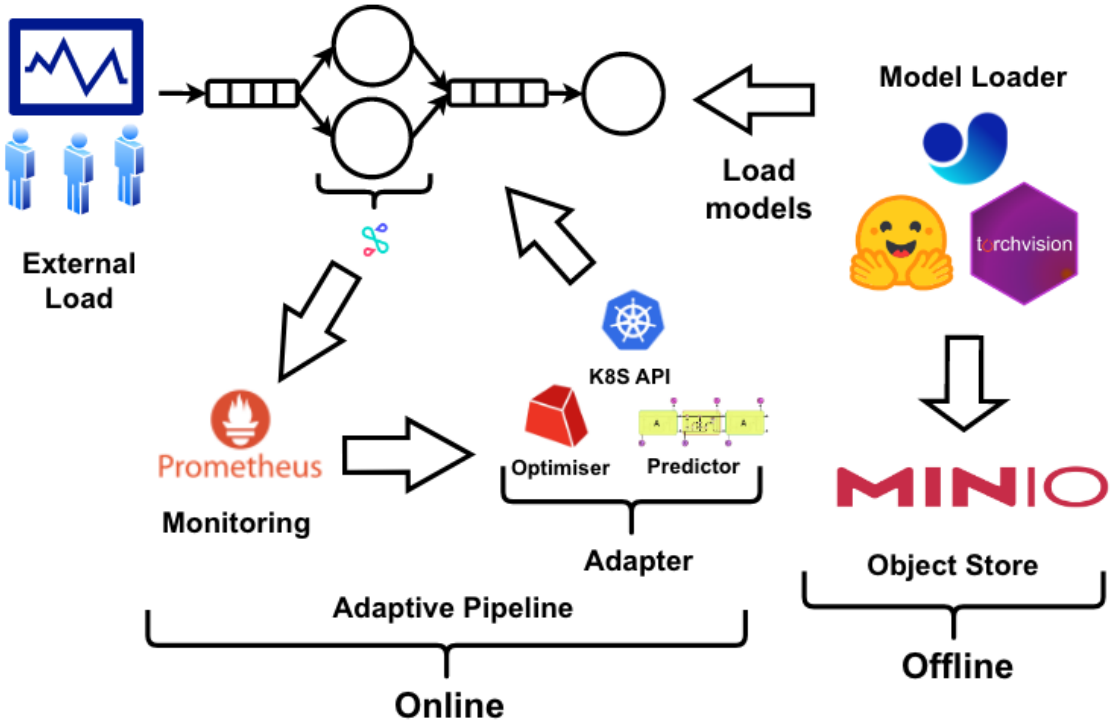


Figure 3.18: Ipa Architecture

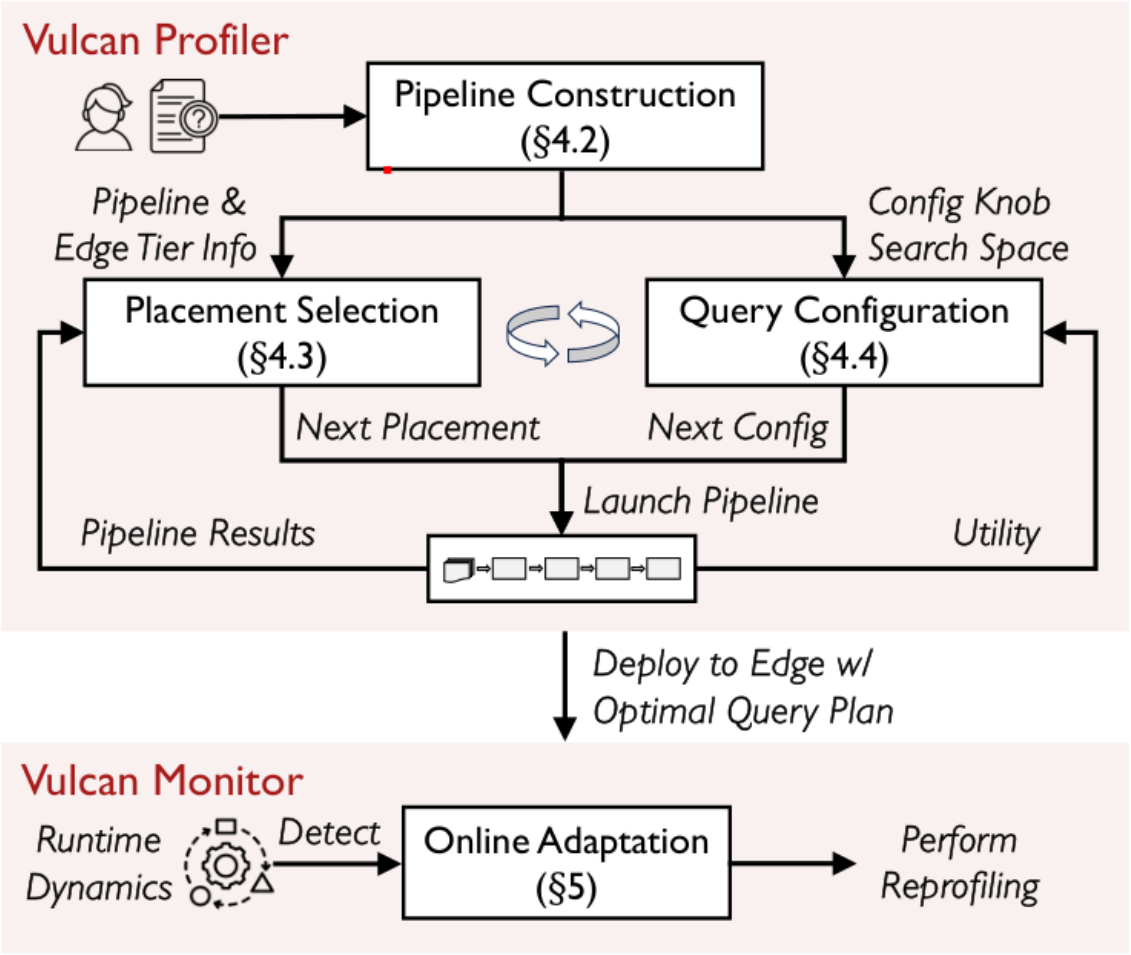


Figure 3.19: Vulcan Architecture

3.1.20 Nvidia Deepstream [27]

Deepstream is commercial product built by Nvidia to help engineers build computer vision pipelines. It includes library of common operators used in computer vision, such as video decoder/encoder, object detector, object classifier, object tracker. The runtime is built on top of GStreamer[28]. Data model is a patch with metadata, or a batch of patches with metadata. Each operator attaches its result of operation as a metadata in the patch, while using metadata of upstream operators. Deepstream is a single node system allowing it to pass patches by reference (No copy), making it extremely fast, allowing real-time analytics.

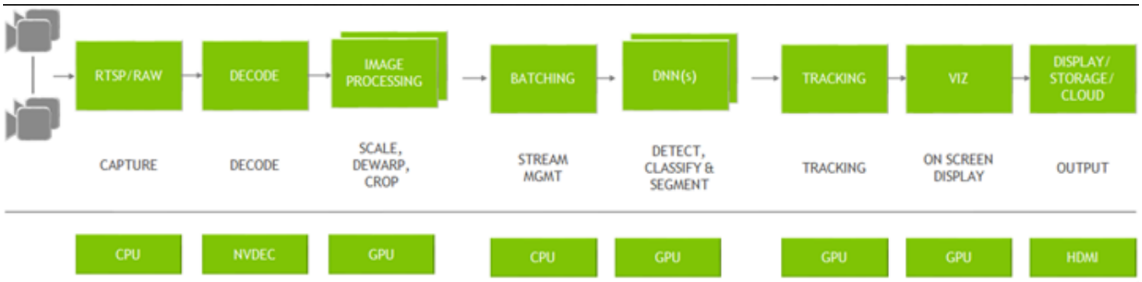


Figure 3.20: Nvidia Deepstream example pipeline

Category	**Systems**
End-to-End Systems	Optasia, Jellybean, DeepLens, Viva, VQPy, IPA
Operator Specific Optimization	NoScope (PM, Detection), Focus (Index, Classification), Tahoma (PM, Classification), BlazeIt (PM, aggregate, limit), Seiden (Index, aggregate), Miris (Index, Tracking), Otif (Index, Tracking)
Distributed Deployment	Chameleon, VideoEdge, DiStream, JellyBean, IPA
Unbounded Vocabulary	Panorama, Zelda

Table 3.1: Related Work Categorization

4 Research Problems

In this section we formulate research problems we will try to solve as part of thesis work.

4.1 Research Problem Statement 01: Predicting end-to-end accuracy of a visual pipeline

4.1.1 Objective

The objective of research work will be to estimate end-to-end accuracy of pipeline given accuracy of individual models numerically. We want the estimated accuracy to be as close to the actual accuracy of the pipeline.

4.1.2 Motivation

Accuracy estimation of a physical plan is crucial for us to be able to pick an optimal plan based on overall accuracy of the pipeline. Typically, accuracy statistics of an individual model is known beforehand, or can be calculated quickly over a validation dataset provided by the user. However, estimating end-to-end accuracy still remains a challenge, which is usually solved by profiling. This will be useful when we are enumerating physical plans for a given logical plan, and want to reject certain plans if they do not meet the accuracy Service Level Agreement (SLA).

4.1.3 Related Work

- **Profiling all possible plans (Jellybean[39])**:- In this method, we profile each model's accuracy while varying its parent models. For e.g., consider a model with two inputs which exhibits the following accuracy profile: (60%,50%) $\rightarrow$ 55%, (50%,60%) $\rightarrow$ 60%, and (70%,90%) $\rightarrow$ 65%, then we can conclude that output accuracy is at least 60% if input accuracy is (55%,83%). This method suffers from exponential search space problem.

- **Approximating relative orderings of the plans (IPA[10])**:- Users could specify an upper limit on latency and ask for most accurate pipeline. In this case we do not need to compute exact accuracy if relative ordering is preserved. Relative ordering can be inferred by just multiplying accuracies of individual models. This works fine if SLA is on latency, but if we are to support accuracy based SLA we have to approximate accuracy as close to actual accuracy possible.

4.1.4 Preliminary Efforts

We are attempting to use Bayesian Network (BN) to model the uncertainity of individual operators and then using the network to eestimate the accuracy of the entire pipeline. This requires solving two challenges:-

- Given the logical plan how to generate the BN?

- Given the BN what is the correct expression of accuracy the user want to optimize?

In experiment-1 the BN is easy to synthesize, however the expression for the accuracy is not as straightforward. In experiment-2 the even the synthesis is non-trivial.

Experiment 1

We create a simple object detection followed by object classification pipeline. Pipeline:- image $\rightarrow$ *DigitDetector* $\rightarrow$ *DigitClassifier* $\rightarrow$ digits. Here image contains one or more digits, *DigitDetector* extract the digit bounding box from the image, and *DigitClassifier* figures out the digit in the bounding box. Accuracy metric for detector is $IoU > 0.7$, which means if $IoU(predicted\_bbox, gt\_bbox) > 0.7$, then it will be considered correct detection. For classifier accuracy is $predicted\_class == gt\_class$. Table4.1 and 4.2 shows the accuracy of detector and classifier respectively. Table shows accuracy of end-to-end pipeline. We try to estimate end-to-end accuracy by simply multiplying individual accuracy as done in [10]. However, we see it is not a close approximation, and it is well below the actual accuracy. Explanation for this is that our correctness criteria for detector is too strict, there are few cases where IoU is well below 0.7 and classifier is still able to classify the digit correctly. But reducing the threshold to say, 0.5 doesn't help either, accuracy does move closer to actual accuracy but not by much, and relative ordering is not preserved anymore.
Instead of simply multiplying we could create a BN shown in Fig4.1. We hypotthesize that this will give a better accuracy estimation. However the removal of independency assumption requires these two parameters $P(correctjIoU0.7)$ $P(correctjIoU > 0.7)$ instead of just $P(correct)$. And we will require more parameters if instead of just two partition $(0.7, 0.7)$

Table 4.1: Trained Detector Accuracy

Detector Name	MAP-50	MAP-70
yolov8-n	0.88	0.53
yolov8-s	0.90	0.551
yolov8-m	0.912	0.559
yolov8-l	0.911	0.561

Table 4.2: Trained Classifier Accuracy

Classifier Name	Accuracy-Top1
yolov8-cls-n	0.87
yolov8-cls-s	0.88
yolov8-cls-m	0.0.89
yolov8-cls-l	0.0.9

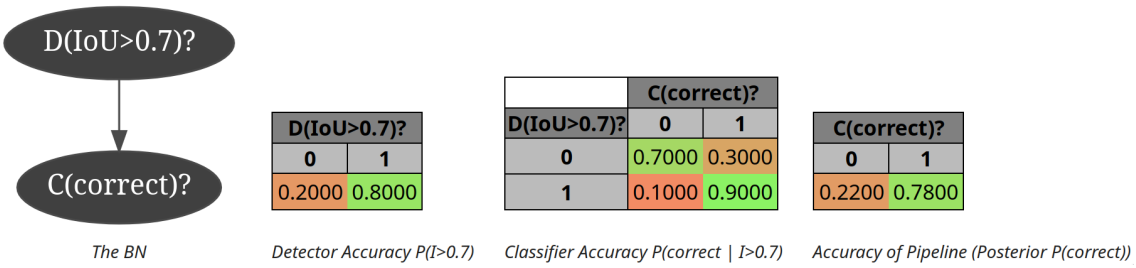
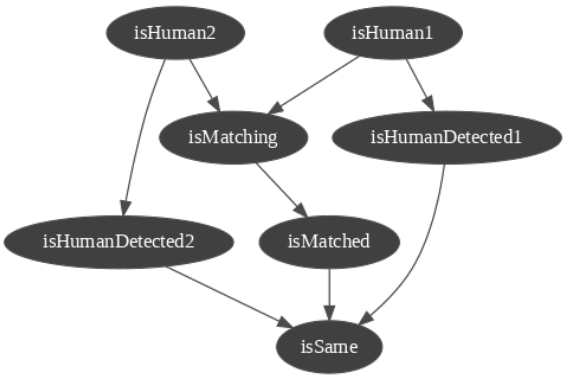


Figure 4.1: Bayesian Network For Experiment-1

Experiment 2

In experiment-1 only one BN was possible (we could change the operator, but that would only effect the probability distribution). In this experiment two different plans and hence two different BN is possible for the same task:- *Pedestrian ReID*.
The two plans are as follows:-



(a) Bayesian Network

isHuman1	
0	1
0.7000	0.3000

(b) Dataset Distribution

		isMatching	
isHuman2	isHuman1	0	1
0	0	0.9000	0.1000
	1	1.0000	0.0000
1	0	1.0000	0.0000
	1	0.9000	0.1000

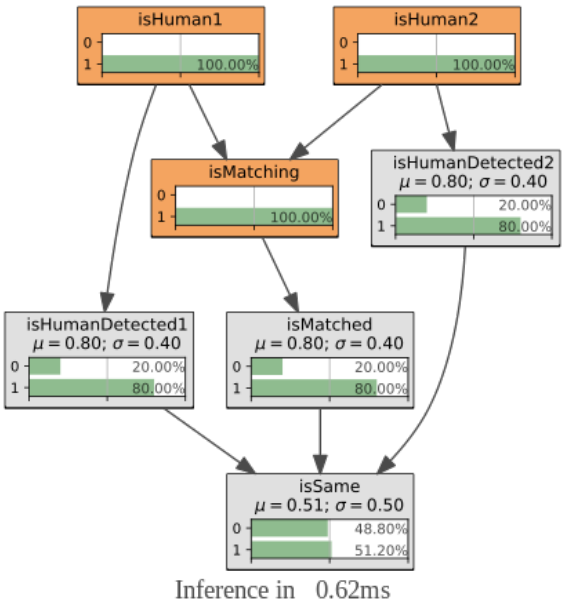
	isHumanDetected1	
isHuman1	0	1
0	0.9000	0.1000
1	0.2000	0.8000

	isMatched	
isMatching	0	1
0	0.9800	0.0200
1	0.2000	0.8000

(c) Model Distribution

			isSame	
isMatched	isHumanDetected2	isHumanDetected1	0	1
0	0	0	1.0000	0.0000
		1	1.0000	0.0000
	1	0	1.0000	0.0000
		1	1.0000	0.0000
1	0	0	1.0000	0.0000
		1	1.0000	0.0000
	1	0	1.0000	0.0000
		1	0.0000	1.0000

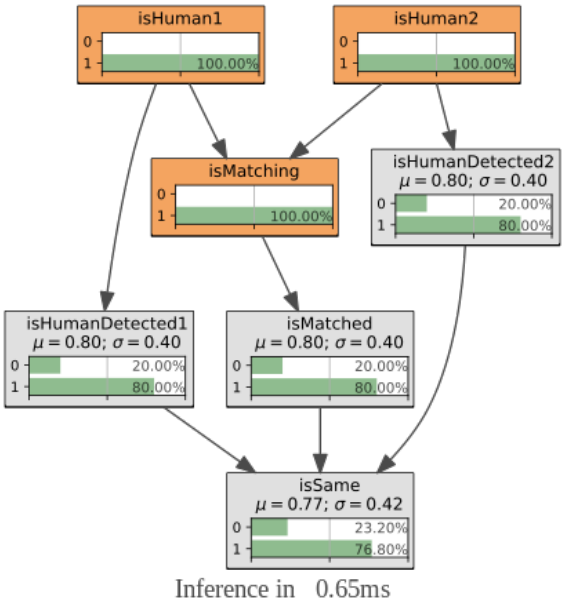
(d) CPT for Filter-Match



(e)
$P(isSame|isHuman1, isHuman2, isMatching)$

			isSame	
isMatched	isHumanDetected2	isHumanDetected1	0	1
0	0	0	1.0000	0.0000
		1	1.0000	0.0000
	1	0	1.0000	0.0000
		1	1.0000	0.0000
1	0	0	1.0000	0.0000
		1	0.0000	1.0000
	1	0	0.0000	1.0000
		1	0.0000	1.0000

(f) CPT for Match-Filter



(g)
$P(isSame|isHuman1, isHuman2, isMatching)$

Table 4.3: End-to-End Pipeline Accuracy

Detectors	Classifier	Actual Accuracy	Estimated Accuracy@MAP50	Estimated Accuracy@MAP70
yolov8-n	yolov8-cls-n	0.68	0.59	0.46
yolov8-n	yolov8-cls-s	0.69	0.61	0.47
yolov8-n	yolov8-cls-m	0.7	0.63	0.48
yolov8-n	yolov8-cls-l	0.7	0.64	0.485
yolov8-s	yolov8-cls-n	0.71	0.62	0.48
yolov8-s	yolov8-cls-s	0.72	0.64	0.488
yolov8-s	yolov8-cls-m	0.73	0.65	0.494
yolov8-s	yolov8-cls-l	0.74	0.67	0.499
yolov8-m	yolov8-cls-n	0.749	0.63	0.488
yolov8-m	yolov8-cls-s	0.76	0.65	0.496
yolov8-m	yolov8-cls-m	0.77	0.67	0.502
yolov8-m	yolov8-cls-l	0.77	0.68	0.507
yolov8-l	yolov8-cls-n	0.75	0.63	0.489
yolov8-l	yolov8-cls-s	0.76	0.65	0.497
yolov8-l	yolov8-cls-m	0.778	0.66	0.503
yolov8-l	yolov8-cls-l	0.785	0.68	0.508

- **Filter-Match** (i) Detect all objects (ii) Filter all pedestrians (iii) Match them with each other using cosine similarity of feature vectors. *i.e.,*

$$isHuman(P_1) \wedge isHuman(P_2) \wedge isMatching(P_1, P_2)$$

.

- **Match-Filer** (i) Detect all objects (ii) Match all objects (iii) If either of the matching objects are pedestrian then consider them similar pedestrian. Note that the assumption here is that a less precise filter can misclassify pedestrian as a non-pedestrian, but the pedestrian matcher will not match pedestrian with some other object. *i.e.,*

$$isMatching(P_1, P_2) \wedge (isHuman(P_1) \vee isHuman(P_2))$$

.

This query was first mentioned in DeepLens[22]. We model the above two plans using BN (fig4.2) and check if it matches the result mentioned in the paper (it did). The plan 1 has faster (it has to process less frames due to the filter). However, plan 2 has higher recall if the filter is less precise (filter will make mistakes, but matcher will correct them). See fig4.2

4.2 Research Problem Statement 02: Automatic visual pipeline synthesis

4.2.1 Objective

Automatically synthesize complex visual pipelines, from minimal specification from user.

4.2.2 Motivation

As logical operators become higher-level, the space of possible physical operators grows exponentially, making them tedious to specify. Specifying all the implementation rules is

necessary to find optimal physical plans. For example, suppose we have a library of vehicle detection pretrained models. Now suppose use wants to extract trucks, and there exists a truck classifier, a smart synthesizer could stitch vehicle detector and truck classifier together to work as truck detector. This of course requires a domain ontology specified by the user that truck is a subclass of vehicle. A type system can be built to capture such semantics.

4.2.3 Related Work

Recently, type-based program synthesis [29, 12, 9] has shown good promise on synthesizing programs from their specifications. We will explore these techniques by treating logical operators as specifications to automatically synthesize implementation rules that map logical operators to physical operators.

4.2.4 Preliminary Efforts

Exploring Nvidia's DeepStream

We explored Nvidia's Deepstream as an physical plan execution engine for visual analytics pipeline. We made the following observations:-

- It is extremely fast. It easily delivers 500fps on a detection tasks.
- It is easy to write a pipeline with existing operators using a declarative syntax.
- However, new operators have to be written in C using Gstreamer and CUDA library, which has learning curve and slows down the development cycle.
- Existing operators are closed source hence we cannot perform any experiments that require us to change the operator itself, and writing one from scratch is hard.
- Although we can send pipeline metrics to cloud, it is not a distributed system all video processing happens on a single node.

We concluded that we deepstream is not research friendly, however we should keep an eye on its progress as a commercial software.

Exploring Apache Calcite [5]

Apache calcite is a (Java) framework that is mainly used for two things:-

- As a **frontend layer** for custom data storage solution. Suppose, we have built our custom data storage solution and want to create a SQL interface for querying it. This will involve creating a lexer, an AST parser, conversion to relational algebra, and finally the execution layer along with optimizations. Using calcite we can avoid building the entire thing from scratch get the SQL interface by only implementing certain interfaces provided by the framework.
- As a framework for writing custom **Query Optimization (QO)** rules. Using calcite we just have to specify our custom QO rules (along with cost heuristics) and calcite will take care of optimization using its inbuilt optimization engine.

We want to use Apache Calcite for writing our optimization rules, but we note that it is built for SQL operations on relation data model. However, the framework is very modular, and we can plug in our custom data model specific to visual queries.

Exploring refinement types using Synquid[29]

A **refinement type** is a type augmented with additional predicate which must be held for all elements of the refined type. The types can be defined as $v : B|P(v)$, where B is the base type, and P is a predicate on values of B. For *e.g.,*all natural number greater than 5 can be written as $\{n \in \mathbb{N}|n < 5\}$. Refinements can enable

4.3 Research Problem Statement 03: Runtime adaption of a visual pipeline in a distributed setting

4.3.1 Objective

Building a system that adapts a running pipeline according to change in data distribution and hardware load/availability.

4.3.2 Motivation

For streaming tasks, the optimal query may not be optimal after a while. For example change in weather condition may hurt accuracy of the pipeline, or execution of some other pipeline on the same hardware may reduce latency. In these cases the pipeline must adapt to satisfy its SLA.
Adaptation can be performed in two different ways:-

- **Changing operator configuration**:- For e.g., loading a different model, or change in image resolution, batch size.
- **Changing operator placement**:- For e.g., moving an operator from edge to cloud or vice-versa depending on hardware load.

4.3.3 Related Work

- **Chameleon**[17]
- **VideoEdge**[16]
- **Distream**[42]

4.3.4 Tentative Approach

Since each VAP can have multiple physical plans, the problem of adaptation is how to switch from one physical plan to another to keep satisfying the accuracy and latency SLOs while minimizing the cloud bill. It is important to keep the switches between plans gradual with the possibility of quickly rolling back switches if the new plan does not work as expected. We build a *Flexiblev Physical Plan (FPP)* that uncovers a broader space of trade-offs and directly facilitates adaptation. FPPs combine multiple complementary physical plans. Compared to using any fixed physical plan, using a flexible physical plan allows gradually moving from one physical plan to another and opens up the space of available physical plans by including mixtures of complementary physical plans. Our key insight is that these mixed plans can provide better trade-offs than individual physical plans, as illustrated by the alternative models and operator placement VAP examples below.

(1) Commutative filters. The first example in Table shows a simple pipeline with two filters denoted by σ_1 and σ_2. For example, we might want to find out when the traffic signal is red (σ_1), and then find out if there are cars on the intersection (σ_2). Since filters can be run in any order, there are two physical plans for this dataflow graph, each running a different permutation of filters.
The flexible physical plan merges these two physical plans into a combined graph. In the combined graph, FPP adds a probability on each edge when it combines the graph: with probability c, the operator *Shoot* sends data (e.g, video frames) to σ_1 (e.g, is the light red?) and with probability $(1 - c)$, it sends data to σ_2 (e.g, is there a vehicle on intersection?). It is clear that switching c from 0 to 1 and vice-versa changes from one physical plan to another.
Adaptation might indeed change c depending on the incoming data. For example, if the light has just turned green, it is better to set $c = 1$, i.e, check for the light being red to quickly discard the frame. Once the light turns red, it is better to set $c = 0$, i.e, first find cars on the road and then verify that the light is red. FPPs allow easily reasoning about different adaptation logic since the adaptation controller just needs to control c. For example, if we already know the light switching schedule at the intersection, then we can just change the value of c based on the schedule. If we have no knowledge of the schedule, we might slowly increase c, when the light is red, to sample some frames in case the light has changed to green.

(2) Operator placement. The first example in Table shows a simple map reduce pipeline, *e.g.,*run object detection on each video frame and count the number of vehicles of each type in 5-minute time windows. There are multiple physical plans depending on the operator placement, such as placing `map` on the cameras or placing it on the cloud. Existing literature on adapting VAPs typically choose one of the two plans. However, neither of the two plans may be optimal. If we place the `map` function on the cameras, the cameras might run out of compute resources thereby not being able to keep up with the frame rate. If we place the `map` function on the server, the camera CPUs might be underutilized and the camera network might start becoming the bottleneck.
These physical plans are merged into a combined FPP while adding probabilities of running appropriate `map` functions. This increases the exploration space of doing adaptation. For example, by setting c_2 to 0.3, camera-2 can offload `map` function for 30% of its frames and process the rest locally.

(3) Alternative models. The next example in Table again shows a simple map reduce pipeline. Here, the `map` function has multiple available implementations denoted by ● and ●, *e.g.,*heavyweight and lightweight object detection models. Hence, there are multiple physical plans: one for each available implementation of `map`.
Again, existing video analytics research switch completely to cheaper implementation, *e.g.,*using the lightweight model, or to the costly implementation, *e.g.,*using the heavyweight model. However, neither of these may uphold the required SLOs. The cheaper plan may satisfy the latency SLO but not the accuracy SLO whereas the costly plan may satisfy the accuracy SLO but not the latency SLO. By setting $c = 0.4$, we can easily run a light weight model for 60% of the frames and run the rest 40% of the frames on the heavy weight model. Doing so opens new design points to satisfy both accuracy and latency SLOs.

5 Conclusion

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