# Deep Video Analytics A data-centric approach to Computer Vision

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# Developments over last 5 years High quality libraries & pre-trained models

- Theano
- Torch
- ROS
- Caffe
- Tensor Flow
- MXNET
- PyTorch
- Deeplearnjs

- Recognition
  - Inception / VGG / Resnet
- Detection
  - R-CNN / YOLO / SSD
- Face detection / recognition
  - MTCNN / Facenet
- Semantic Segmentation
  - Multipathnet / FCN / CRFasRNN

## Developments over last 5 years A deluge of datasets!

- Open Images
- Yahoo Flickr Creative Com. 100M
- MSCOCO
- ViCom
- Visual Genome
- YouTube-BoundingBoxes / 8M
- AMOS

- imSitu, Charades by AllenAl
- KITTI /Toronto City
- Udacity car dataset
- Caltech, INRIA, ETH Pedestrians
- Stanford Drone Dataset
- Uber text
- THUMOS

Number of datasets ≅ Number of research groups With each dataset having its own JSON or XML format, incompatible with all others.

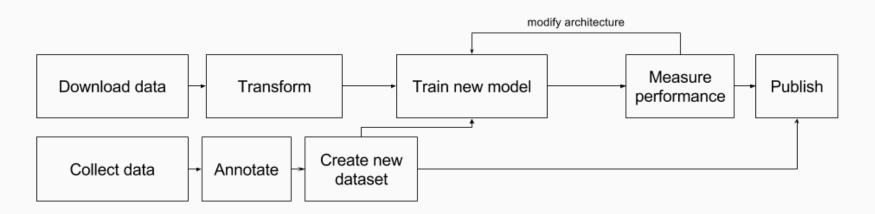
## What else changed over last 5 years?

- Container ecosystem (Docker, Kubernetes) enables deployment of complex applications.
- Ability to scale quickly by adding compute capability (including GPUs) billed at minutes / seconds resolution.
- Flexible cloud storage options. (S3, EBS & EFS)

## What is hidden in plain sight?

#### Model-centric approach

Libraries & frameworks are designed with **goal of training and evaluation of models for individual tasks**.



Unsuitable for building systems that learn in interactive manner, or leverage data from multiple sources or combine multiple tasks.

# We need a data-centric approach that allows us to combine

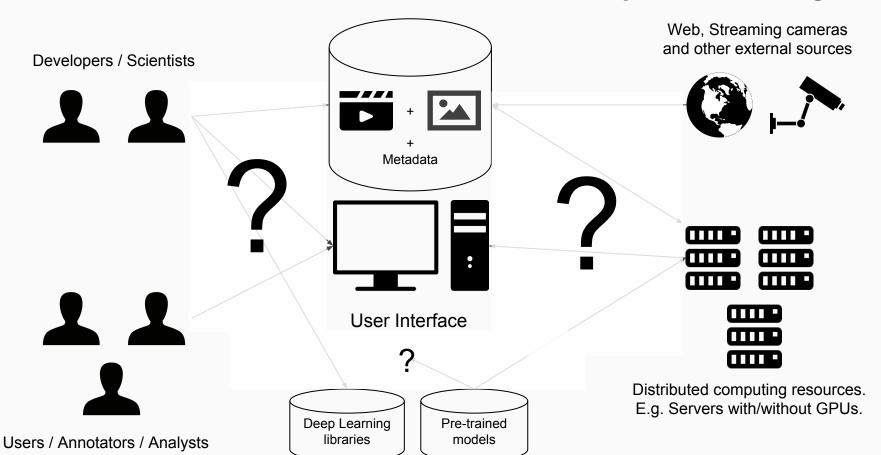
- Models for multiple tasks
- Data from multiple sources
- User Interaction / interface

#### A Relational Model of Data for Large Shared Data Banks. By Edgar F. Codd

Can we develop an equivalent of relational model for visual data?

Relational data: Postgres, MYSQL, SQLite
::
Text, HTML: Lucene/Solr, Elasticsearch
::
Videos & Images:

#### How do we structure Visual Data processing?



## Previous attempts: LIRE project

- LIRE: Lucene Image Retrieval
  - http://www.lire-project.net/
- Developed pre-Deep Learning
- Functionality limited to computing & storing feature
   vectors such as Color Layout, Edge Histogram, etc.

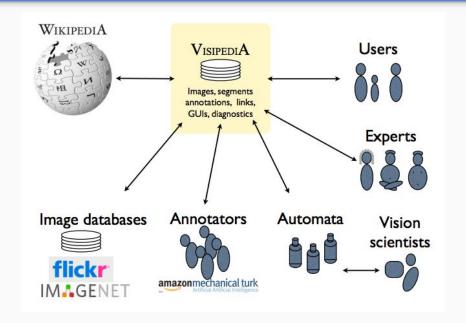
### Previous attempts: CloudCV

- Large Scale Distributed Computer Vision as a Cloud Service
- Support for OpenCV, Graphlab, Cafe
- Image Classification, VQA, stitching, etc
- Does not retains state. E.g. you cannot store images.

### Previous attempts: NVidia DIGITS

- "DIGITS (the Deep Learning GPU Training System) is a webapp for training deep learning models."
- Load/create datasets, train models, deploy models.
- Aimed at researchers
- Written in Python/Flask with Torch & Caffe supported

#### Previous attempts: Visipedia



### Previous attempts: Visipedia

- Collaborative creation of visual data
- Pre-defined set of concepts E.g. Birds, Trees
- Different type of participants
  - Experts, Annotators, Citizen Scientists, Users, Computer scientists
- Retains state

### Previous attempts: VMX.ai

- Underfunded Kickstarter project Circa Jan 2014
- by Tomasz Malisiewicz
- Pre Tensor Flow, Pre Deep Learning
- Allow developers to create real time detectors
- Support for training model

## Quick summary

- LIRE: limited functionality (Lucene add-on)
- CloudCV: Provides a service, cannot retain "state"
- NVidia Digits: Intended for training not inference
- Visipedia: Intended to be a monolithic deployment

#### Few ongoing attempts

- Scanner by Alex Poms (CMU) & Will Crichton (Stanford)
  - https://github.com/scanner-research/scanner
- Kitware Image and Video Exploitation and Retrieval
  - https://github.com/Kitware/kwiver
- VISE project by Oxford VGG group
  - https://gitlab.com/vgg/vise

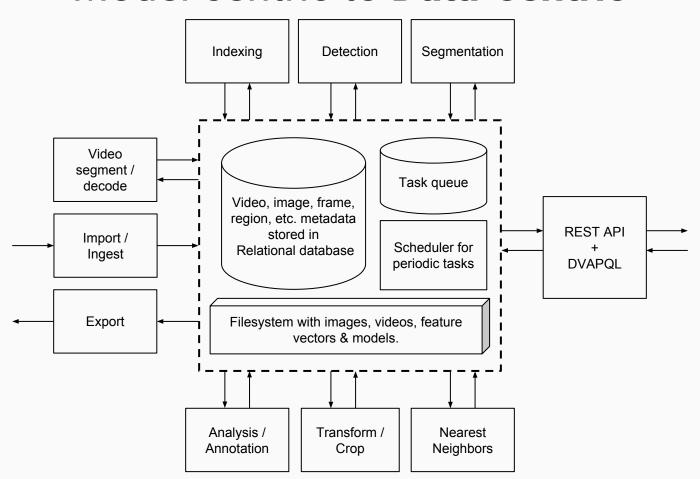
Relational data : Postgres, MYSQL, SQLite ::

Text, HTML: Lucene/Solr, Elasticsearch

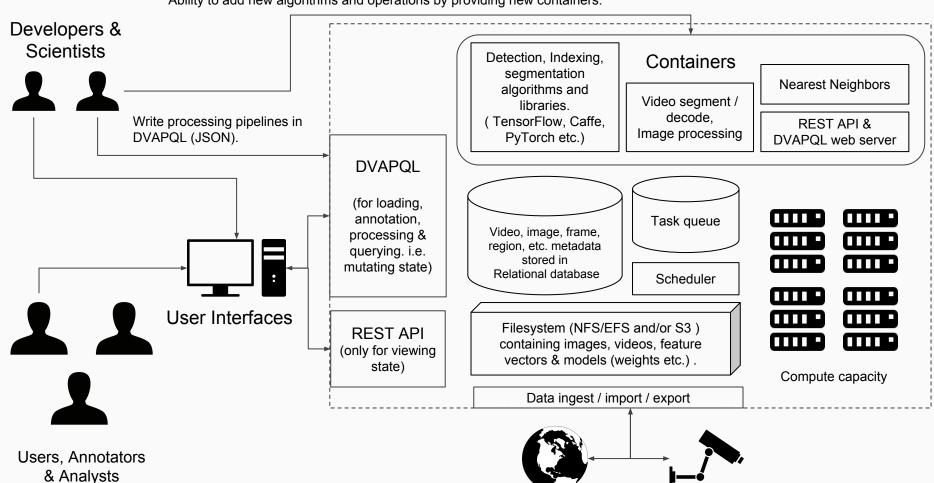
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Videos & Images: Deep Video Analytics

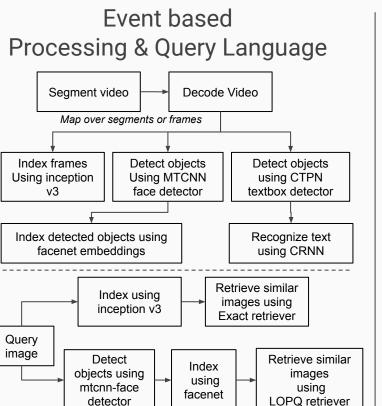
#### Model-centric to **Data-centric**

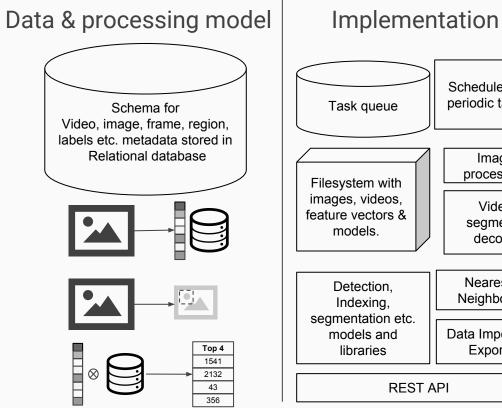


Ability to add new algorithms and operations by providing new containers.



#### We provide all three!





Scheduler for

periodic tasks

Image

processing

Video

segment /

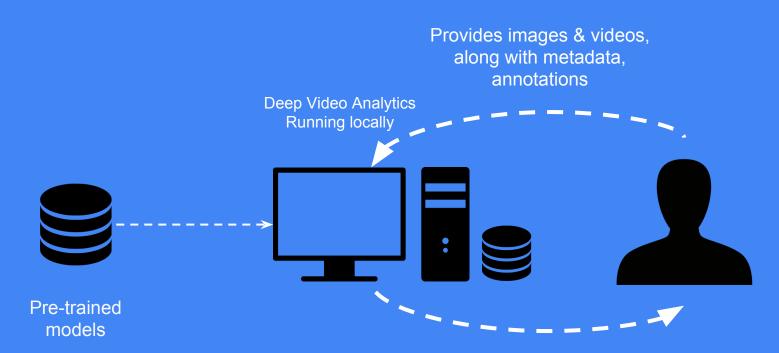
decode

Nearest

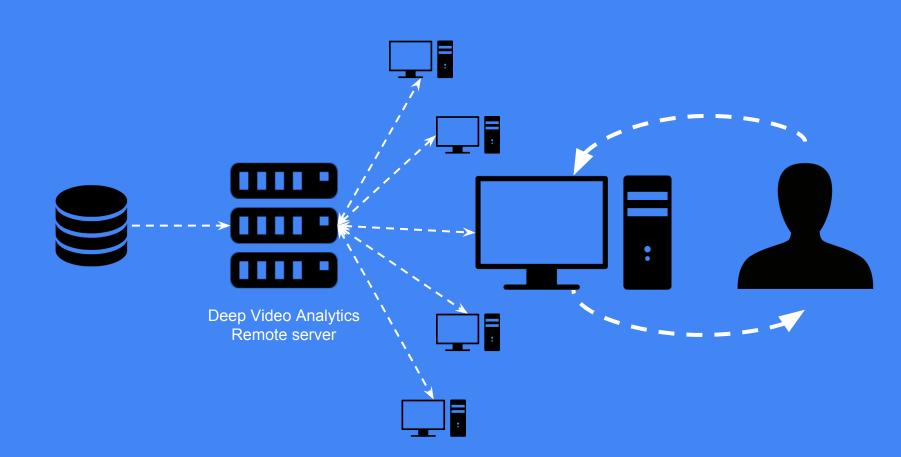
Neighbors

Data Import &

Export



Analyzes information about detected objects, performs queries to retrieve similar images / objects.



#### Design goals

- Usable by non-researchers
- Visual Search as a "Primary User Interface"
- Users can provide data easily (via upload, youtube-dl, annotation UI etc.)
- Batteries-included approach with an indexing and detection pipeline
  - o Tensor Flow Inception v3, VGG-16, Single Shot Detector trained on COCO
  - Face detection / alignment / recognition
  - Deep OCR using CRNN & CTPN. Train new detectors using YOLO+Keras.
- Pre-indexed datasets from different domains can be quickly loaded
- Can be easily customized by developers & researchers.

#### Technical goals

- Useful without having to write code or config
- Works on machines with and without GPUs
  - Works (albeit slowly) without a GPU, tested on Linode VPS with 8Gb RAM & 4 Cores
- Handles uploads and continuous index updates
- Data can be easily imported, exported and shared
- Can be easily modified by technical users
  - o E.g. Adding more operations to processing pipeline
- Can be scaled out by adding more GPUs / Machines

#### Frameworks & libraries used

- Django, Postgres, Celery, RabbitMQ, Docker, NVidia-Docker
- Tensorflow (primary), PyTorch, OpenCV, FFmpeg, LOPQ & Caffe



# What are the core primitives for Visual Data Analytics?

#### Visual Data

E

{ Images, Videos, Annotations, Features}

#### Data & Processing

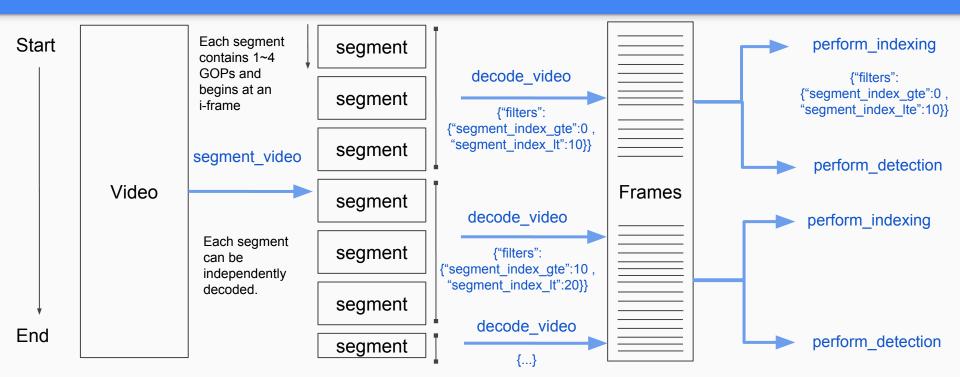
#### Data

- Video / Segment
- Dataset
- Frame / Image
- Regions over an image
- Tubes over sequence of images
- Feature vectors
- Audio

#### Processing

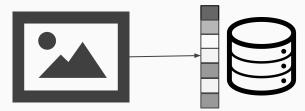
- Video Segmentation + Decode
- Image processing
  - Indexing / Detection / Segmentation / Analysis
- Vector processing
  - Retrieve nearest neighbor / Build K-NN graph
- Image transformation
  - Crop / Resize / Align / Apply segmentation mask

# Video processing Parallelized segment + decode pipeline



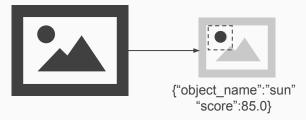
## Frame/Region processing operations

#### Indexing



Compute feature vector such as Inception pool, embedding, RGB histogram etc.

#### **Detection**



Detect objects and return bounding boxes

#### **Analysis**



Analyze image/region and generate metadata (E.g. text description) and/or label

#### Segmentation



Compute pixel-wise mask using semantic segmentation, superpixels etc.

#### Vector processing operations



Given feature vector find K-Nearest Neighbors

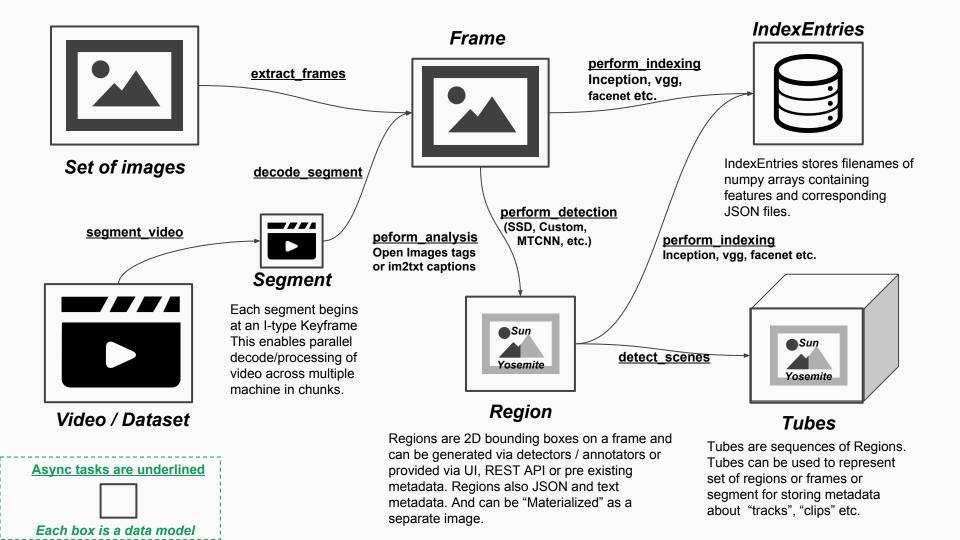
Given a set of vectors generate K-NN graph

Leverage latest open source implementations for approximate & exact Nearest Neighbors

- Yahoo Locally Optimized Product Quantization (Apache)
- Facebook Al Similarity Search (BSD + PATENTS restrictions)

# Data & Processing Key insights

- Different operations have different requirements
  - In terms of number of computations and memory
  - Segmentation > Detection > Indexing / Analysis
- Also different I/O access patterns
  - Detection & Analysis does not requires writing to file system only DB and read
  - Indexing requires writing to filesystem to store computed vectors
  - Segmentation requires writing to filesystem to store computed masks as .png files
- By separating operations we can reason about hardware requirements



### DVAPQL

#### Deep Video Analytics Processing & Query Language

- Specified in JSON
- Launch multiple hierarchical tasks
- Three types of processes
  - Query
    - Retrieve similar images, etc.
  - Process
    - Import video, index images, detect, etc.
  - Schedule
    - Monitor video stream, etc.
- REST API for viewing state & submitting DVAPQL

```
Example
{ "process_type" : "V", "tasks": [
{"operation": "perform_video_segmentation", ... ]}
{ "process_type": "Q", "b64_image_data":".....",
"tasks": [ {"operation":"perform_indexing", ...
{ "process_type" : "S", "tasks": [
{"operation":"ingest_video", ... ]}
```

## A task based hierarchical processing model

```
{"operation": "perform_detection", "arguments": { "filters": "__parent__", "next_tasks": [] }}
             {"operation": "perform_transformation", "arguments": { "op":"crop", "filters":
                           {"event_id":"__parent_event__"}, "next_tasks": [] }}
{"operation": "perform_indexing", "arguments": {
                                                         {"operation": "perform_indexing", "arguments":
"filters": {"event_id" : "__grant_parent_event__",
                                                         { "filters": {"event_id" :
"w_gte" : 50, "h_gte" : 50 }, "indexer": "vga" }}
                                                         "__grant_parent_event__", "w_gte": 50, "h_gte"
                                                         : 50 }, "indexer": "inception" }}
```

All above tasks run on a specific video / dataset which is not shown for brevity.

## Queues for optimal task processing

- Different tasks have different requirements
  - Retrieval / Nearest neighbors: High Memory for storing Index / Approximate index
  - Indexing : GPU for computing embeddings
  - Detection / Segmentation : GPU with higher memory
  - Video decode: GPU optional
  - Crop / Transform / Extract : CPU
- Primitives for Queue management
  - launching queues
  - Monitoring GPU Memory utilization / allocation

## Routing tasks Two methods according to memory use

#### Routing by task name

- Used for routing task without persistent memory use between tasks.
- E.g. perform\_dataset\_extraction, perform\_video\_decode, perform\_clustering etc.
- There is no state/memory that persists between tasks.
- q\_extract, q\_clusterer, q\_trainer

#### Routing by model & task name

- Used for routing task with persistent memory use between tasks.
- E.g. perform\_retrieval, perform\_indexing, perform\_detection
- Above tasks require keeping model, index in memory. Crucial to avoid model loading overhead and memory use under control.
- q\_indexer\_1, q\_retriever\_1, q\_detector\_3

# Launching workers at container launch vs. dynamically

#### Via **environment variables** at container launch

- Launch by queue\_name
   E.g. LAUNCH\_Q\_qextract=1
- Launch by model name and task type (indexer/retriever/detector, etc.) E.g. LAUNCH\_BY\_NAME\_indexer\_inception, LAUNCH\_BY\_NAME\_retriever\_inception, LAUNCH\_BY\_NAME\_detector\_coco
- Model name gets replaced by the primary\_key in the database at launch.

#### Dynamically via **perform\_host\_management**

- Launch dynamically by sending message to any host on q\_manager
- Launch task "perform\_host\_management"
   With arguments specifying host\_name and queue\_name to consume.
- Used when new detector, indexer, analyzer, etc. models are created. Also to dynamically shutdown workers to free GPU memory.

## Code organization dvaui, dvaapp & dvalib

#### dvaui: a django app

Search, Annotation & Admin UI

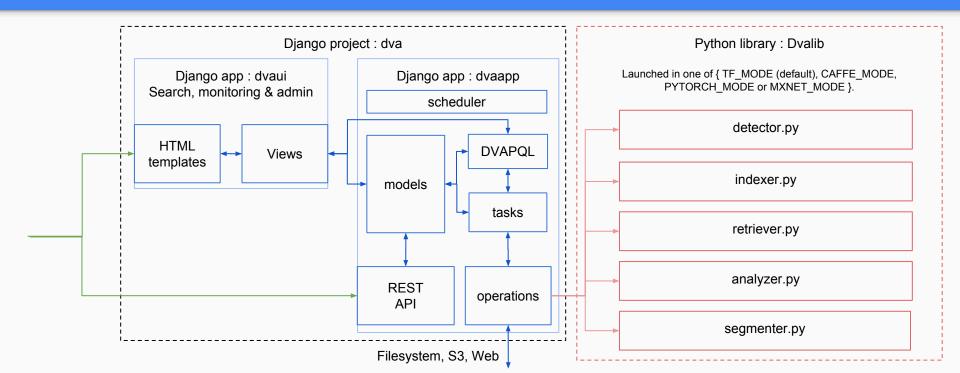
#### dvaapp: a django app

- Data model / REST API
  - Video, Frame, Region, Query Event, Process etc.
- DVAPQL processing using Celery
  - o Perform tasks, manage queues
  - Monitor resource use
- Uses dvalib to carry out tasks

#### dvalib: library with implemented model

- Goal: ensure uniform interface
- Database & Message queue agnostic
- Defines interface & implementations for
  - Detection / Indexing / Segmentation / Analysis
  - Retrieval & training
- Implements models that use TensorFlow (Default), PyTorch, MXNet and Caffe
- Can be tested independently

## Code organization: dvaui, dvaapp & dvalib All in a single container



## Emulating datacenter on a machine

Docker enables same codebase across all configurations (a laptop, multi-GPU machine, datacenter)

Docker-compose used for simulating distributed environment for testing and single machine deployment

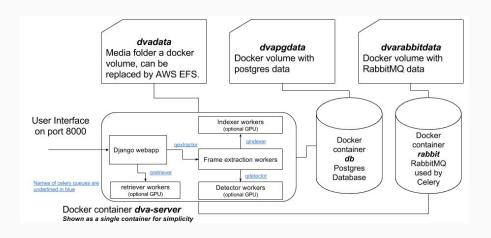
#### Docker container image and :tags

- dva-auto:latest (CPU Tensorflow + PyTorch)
- 2. dva-auto:caffe-cpu (CPU Caffe)
- 3. dva-auto:gpu (GPU Tensorflow + PyTorch)
- 4. dva-auto:caffe (GPU Caffe)

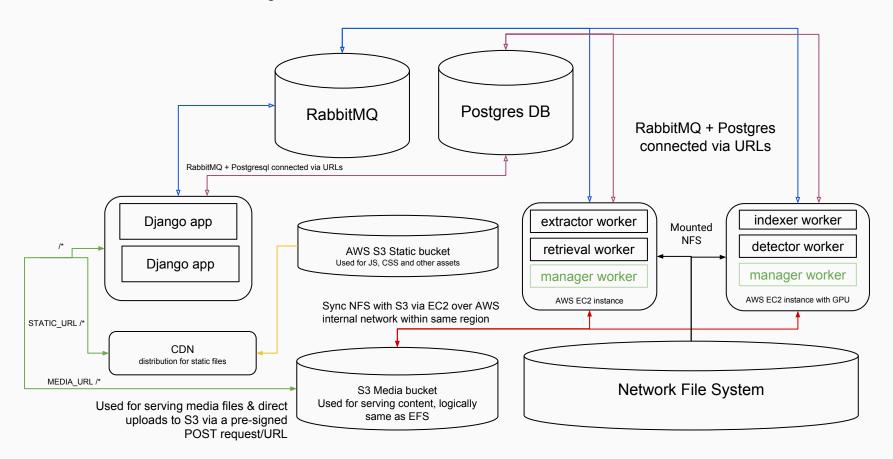
All images are automatically built on docker hub

#### Docker volumes

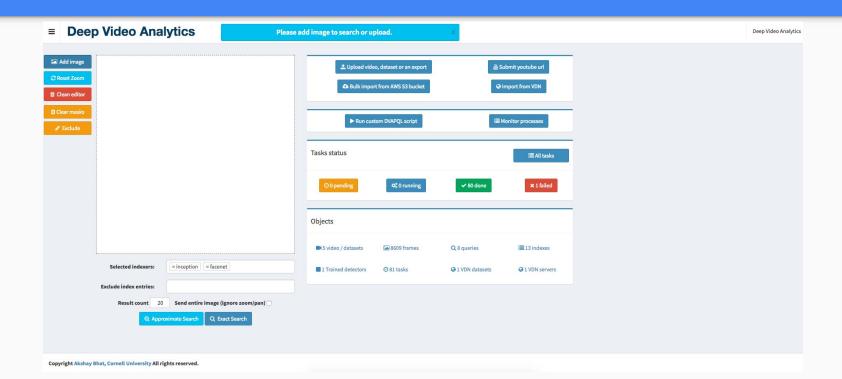
- 1. dvadata / shared file-system
- 2. dvapgdata (when DB is containerized)
- 3. dvarabbitdata (when rabbitmq is containerized)



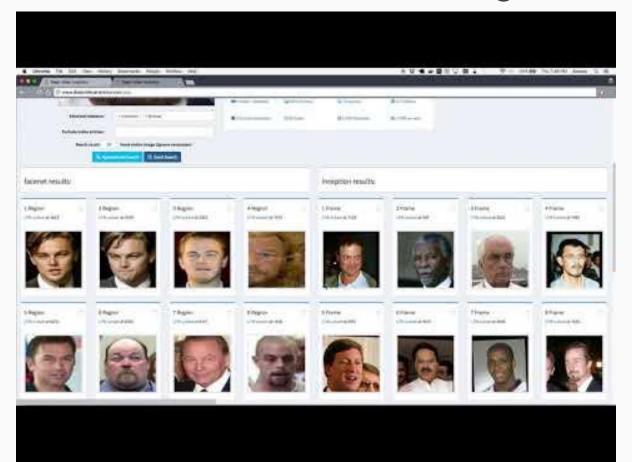
### Scalability with distributed architecture



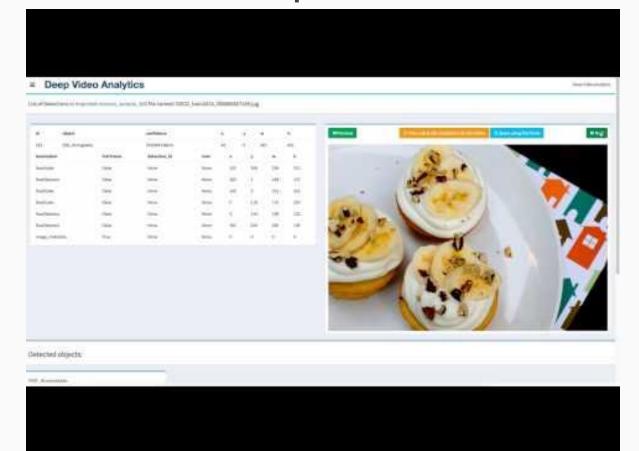
### User Interface



## Latest version beta, 17<sup>th</sup> August 2017



## 7<sup>th</sup> April 2017



### 15<sup>th</sup> March 2017



People: Facebook

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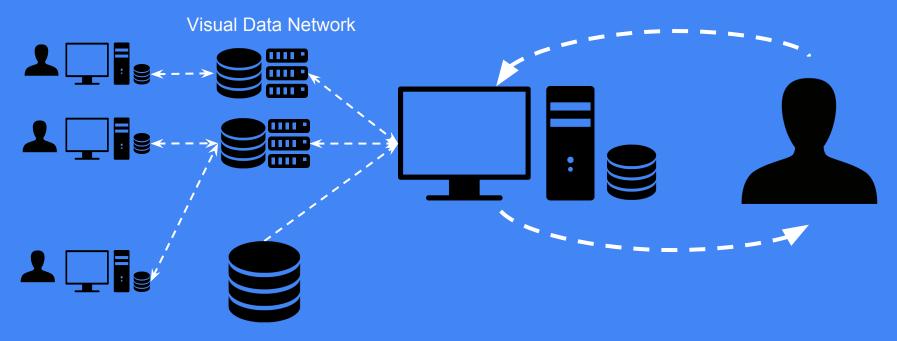
Code: Git / GitHub, GitLab

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Visual Data: Visual Data Network

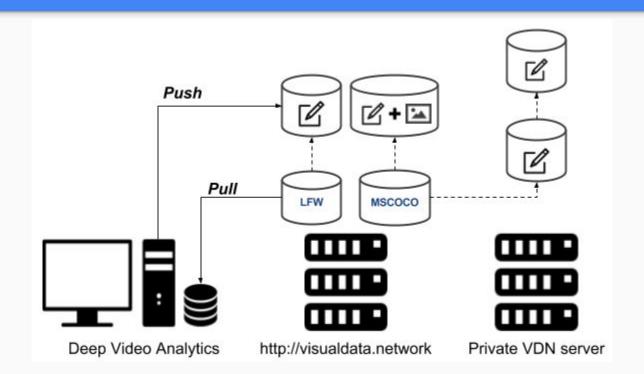
### Sharing data using Visual Data Network

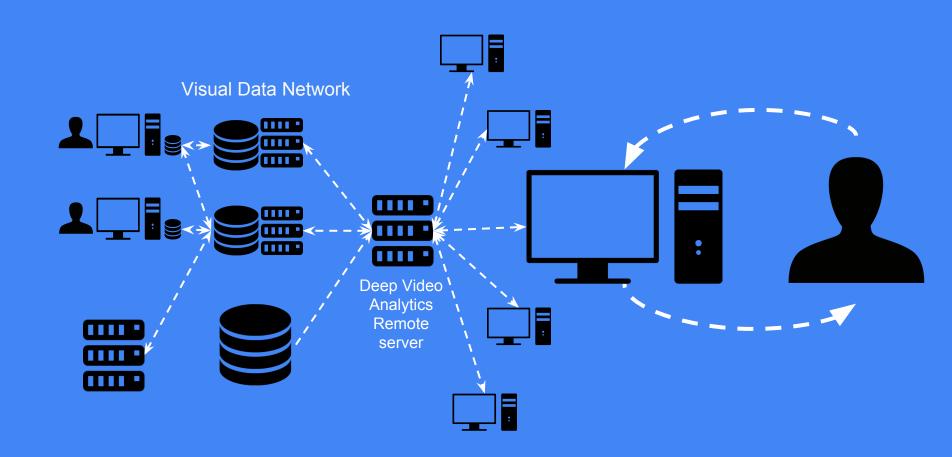
Import & export new datasets / annotations share with other users



### Visual Data Network enables seamless sharing

Push, Pull video / dataset, Annotations, just like you would with GitHub





## Open questions: A work in progress

- How to effectively manage GPU memory & utilization?
- How to balance fast/static vs slow/dynamic indexes?
- How to learn continuously from annotations/feedback?
- How to minimize storage requirements via compaction?
- How to enable Real time processing?

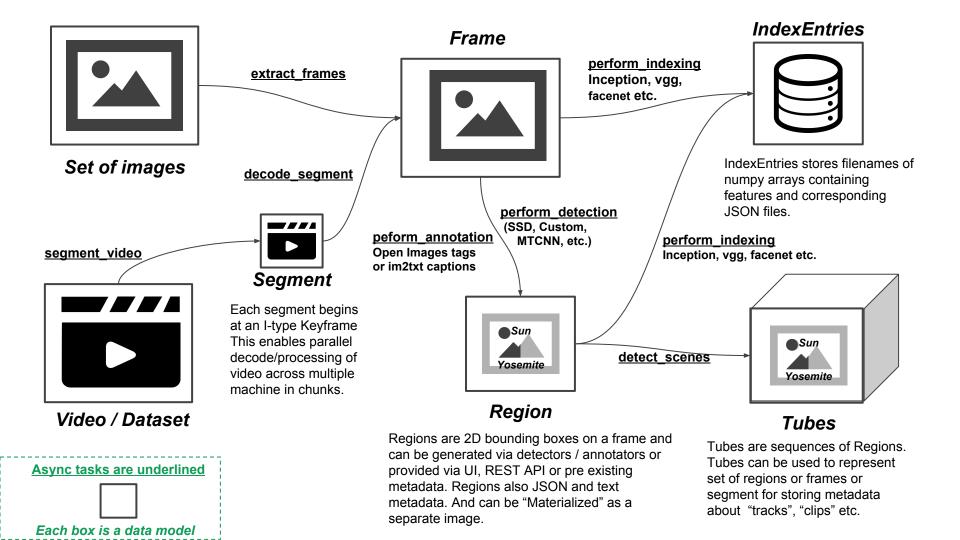
## Thanks!

Contact me

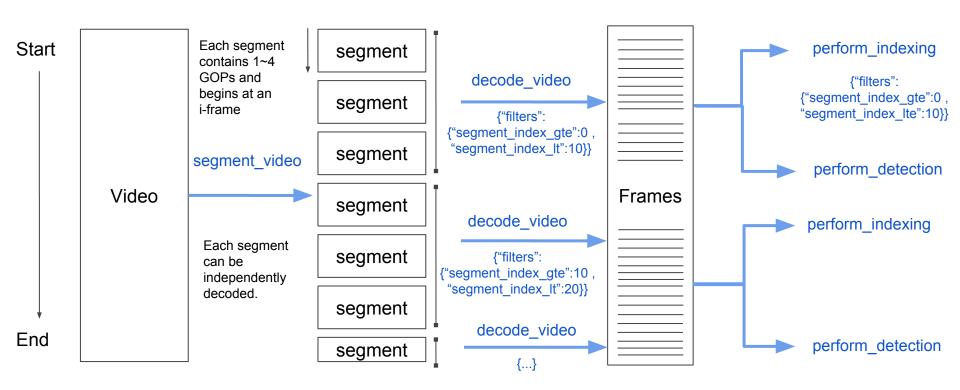
akshayubhat@gmail.com

www.akshaybhat.com

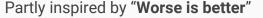




## Distributed processing using hierarchical tasks



#### Software Development approach or "How I developed Deep Video Analytics"



- Start at "final scale" at which it's intended to be used
  - Easy to optimize each component, difficult to change architecture.
- Write "high level" tests rather than "unit tests"
  - E.g load video -> extract frames -> build index -> query
- Observability is crucial, develop UI for visual inspection
- Create start-from-zero config and use it for manual verification
- Keep everything in a single repo (including User Interface)
- DO NOT write a new database or roll your own message queue
  - Both Postgres and RabbitMQ are natively / cheaply supported in Travis / Heroku
  - o It's a nightmare to debug concurrency primitives also difficult to convince others to trust / maintain your code.
- Optimize for one goal (Features, Correctness, Consistency, Simplicity) at a time ( over days / week )
  - E.g. Trade consistency/quality when adding new features. Once feature is done/verified/popular improve code quality.
     Once code quality has improved, transition to a more consistent / simple model. Use consistency to add new features.

