



Video Processing on Serverless

Group 15

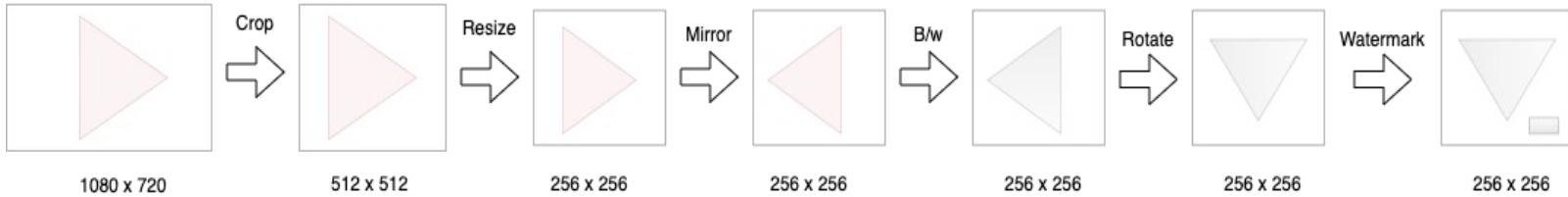
Mohit Shah (A59005444)

Gursharan Ahir (A59012151)

Soham Pachpande (A59001664)

Video Processing Pipeline

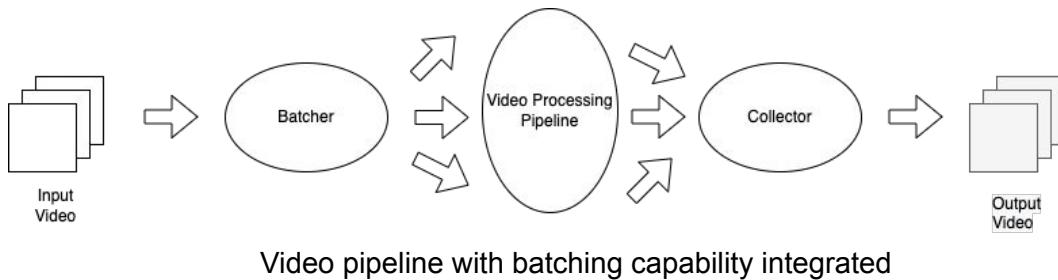
- The pipeline performs operations like crop, rotate, mirror etc. on a given input video in order to synthesise data for ML-related applications
- The pipeline is implemented using ffmpeg-based moviepy¹ python library



1- <https://pypi.org/project/moviepy/>

Batching

- Irrespective of the memory-cpu configuration, the serverless video pipeline would timeout for videos greater than a threshold (since lambda has 15 minutes timeout)
- We introduce batching and collection mechanism with variable batch length to support even larger input videos



movieipy-video-batch [Info](#)

Objects | Properties | Permissions | Metrics | Management | Access Points

Objects (15)
Objects are the fundamental entities stored in Amazon S3. You can use [Amazon S3 Inventory](#) to get a list of all objects.

[Copy S3 URI](#) [Copy URL](#) [Download](#) [Open](#) [Delete](#)

Find objects by prefix

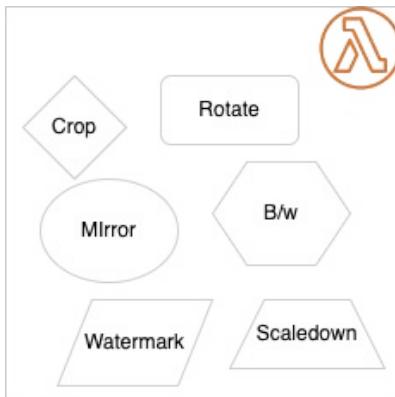
	Name
View	ElephantsDream_1_6_batch_cropped_resized_mirror_bw_rot_watermarked.mp4
View	ElephantsDream_1_6_batch.mp4
View	ElephantsDream_2_6_batch_cropped_resized_mirror_bw_rot_watermarked.mp4
View	ElephantsDream_2_6_batch.mp4
View	ElephantsDream_3_6_batch_cropped_resized_mirror_bw_rot_watermarked.mp4
View	ElephantsDream_3_6_batch.mp4
View	ElephantsDream_4_6_batch_cropped_resized_mirror_bw_rot_watermarked.mp4
View	ElephantsDream_4_6_batch.mp4
View	ElephantsDream_5_6_batch_cropped_resized_mirror_bw_rot_watermarked.mp4
View	ElephantsDream_5_6_batch.mp4
View	ElephantsDream_6_6_batch_cropped_resized_mirror_bw_rot_watermarked.mp4
View	ElephantsDream_6_6_batch.mp4
View	ElephantsDream_ProcessedAggregated.mp4
View	ElephantsDream.mp4
View	logo.png

S3 bucket with objects created by our batching capability integrated video-processing pipeline

Approaches

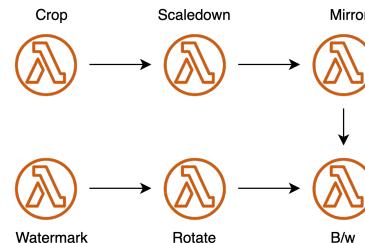
Monolithic

- All stages within a single Lambda function



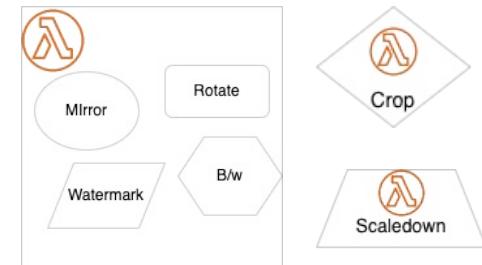
Manual Splitting

- Separate Lambda Functions for each independent step



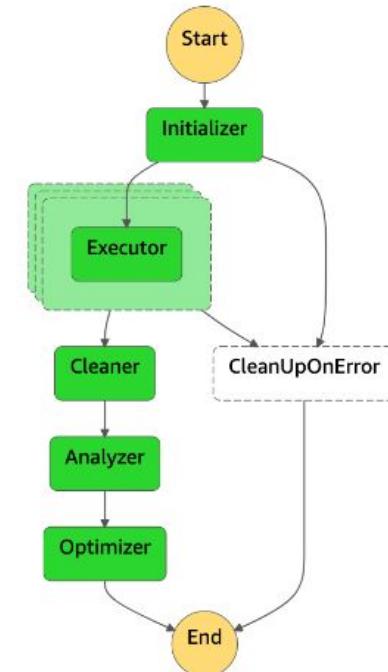
Strategy-based Splitting

- Aggregating Small Video Processing Steps



AWS Step Functions and Log Insights for Profiling

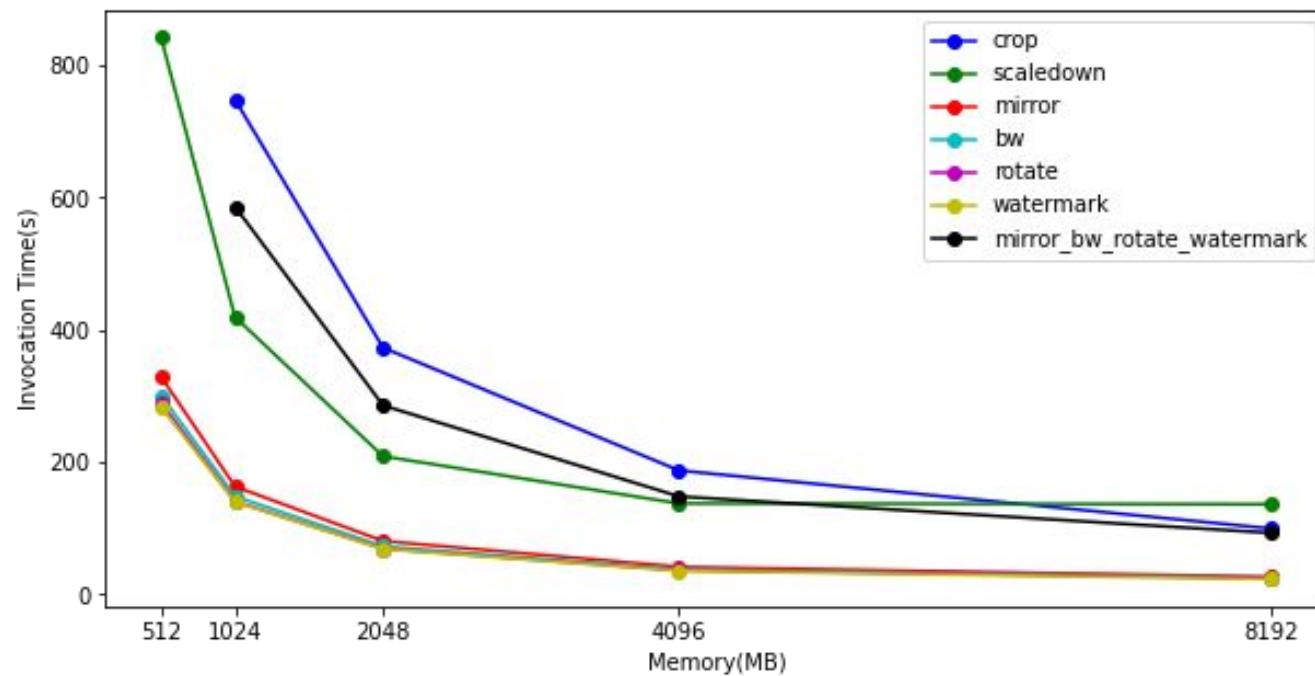
- AWS Step Functions allows users to orchestrate workflows on AWS Lambda as per defined configuration
 - We used Lambda Power Tuning¹
- Allowed us to rapidly experiment with various Lambda configurations of our video processing pipeline
- Deployed ~120 Step Function Executions on over 20 Lambda functions
- AWS Cloudwatch Log Insights allowed us to analyze memory utilisation of our Lambda functions



Lambda Power Tuning State Machine

1 - <https://docs.aws.amazon.com/lambda/latest/operatorguide/profile-functions.html>

CPU Profiling



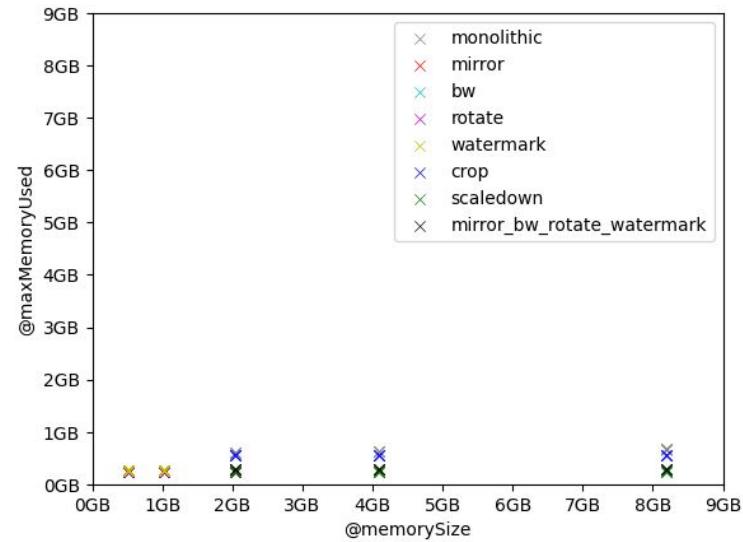
Memory Profiling

All Functions had low memory % utilization...

BUT Functions timeout for lower memory configuration...

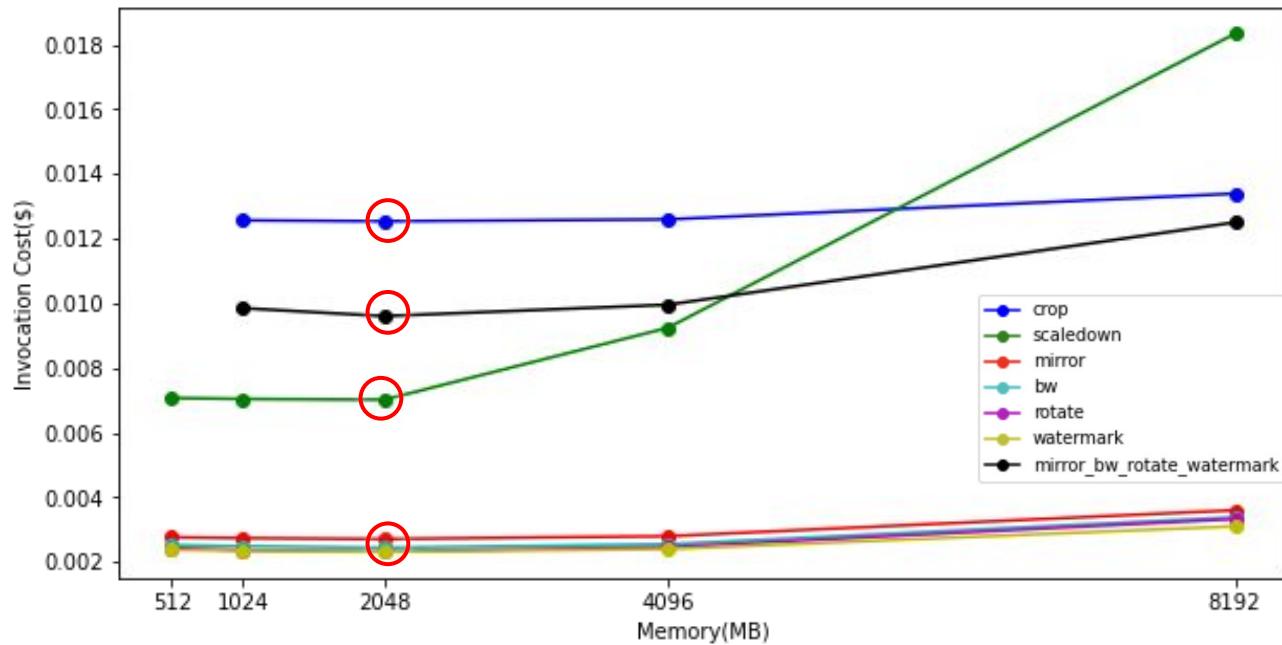


The infamous fixed CPU-Memory ratio



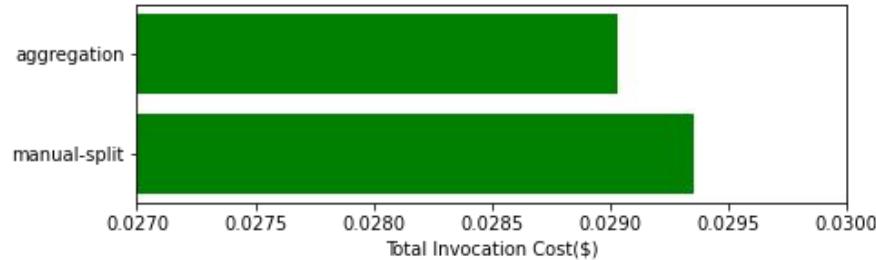
Memory Consumption of Various Lambda Functions

Cost Profiling



Results

- The cost-performance optimal memory allocation was found to be **2048MB**
- The estimated cost benefit of aggregation over manual-splitting for 1 billion invocations would be **\$320k**



Conclusions

Monolithic

- + Good for Small Videos and Small Applications
- + No intermediate storage interface required
- Timeout for larger videos
- High cost for less intensive memory processes

Manual Splitting

- + Right-size each stage
- + Handle larger videos
- Intermediate Storage introduces latency and costs
- Underutilized Compute Resources

Strategy-based Splitting

- + Right-size each stage
- + Handle larger videos
- + Better Resource Utilization
- Finding splits is non-trivial

Q/A