Fast and Accurate Image segmentation

for medical imaging data

Team 17
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00

Objective

Parallel Fast and Accurate
Image Segmentation on Cell Nucleus

Image Segmentation of Cell Nuclei

Data source: 2018 Data Science Bowl challenge

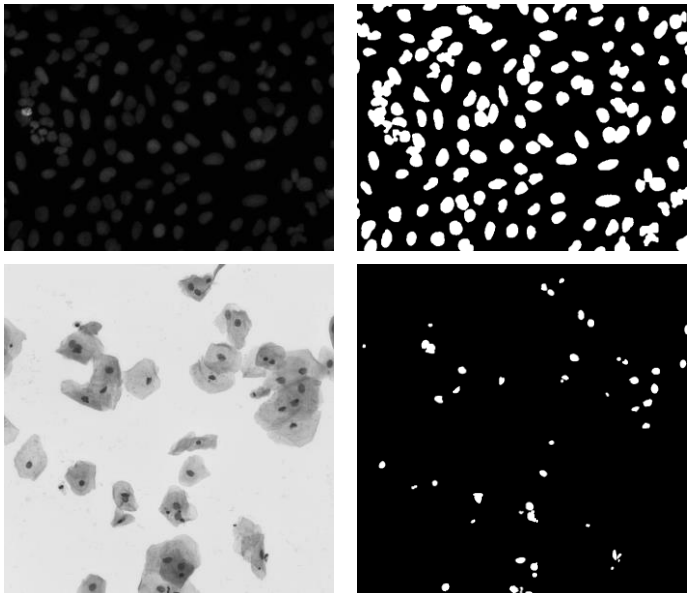
670+ **Training set**

Images of different cell types and tissues

~65 **Test set**

Without ground truth masks

Original image **Ground Truth Masks**



Application Type

An offline, compute intensive toolbox for nuclei segmentation which

- Provides **three** segmentation models:
  - **Otsu's Method** (threshold method implemented in C++)
  - **Boruvka's Algorithm** (tree-based method implemented in C++)
  - **UNet** (Keras + Tensorflow deep learning in Python)
- Allows fast nuclei segmentation for new images
- **Big Compute + Big Data** (more on the former)
- **Cloud infrastructure:** Google Cloud (VM and cluster)

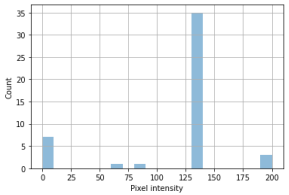
01

Otsu's method

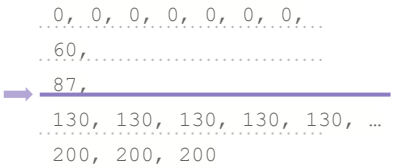
Otsu's Method Algorithm overview

Read image

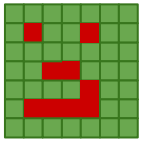
Pixel intensity hist.



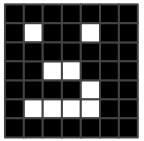
Find threshold



Final segmentation



Write result



Step 0:
Read in image

Step 1:
Build the histogram of pixel intensity.

O(N)

Step 2:
Exhaustive search of threshold to minimizes inter-class variance.
*O(256*256) ~ O(1)*

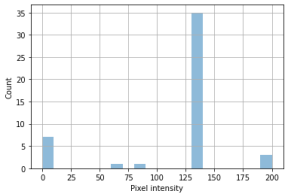
Step 3:
Final image segmentation based on the threshold.
O(N) complexity

Step 4:
Write out image result

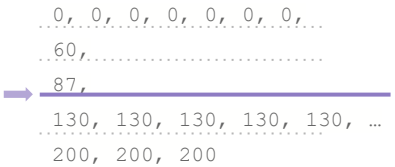
Otsu's Method Algorithm overview

Read image

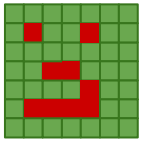
Pixel intensity hist.



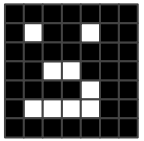
Find threshold



Final segmentation



Write result



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*O(256*256) ~ O(1)*

Step 3:
Final image segmentation based on the threshold.
O(N) complexity

Step 4:
Write out image result

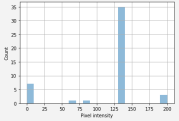
- **Language:** C++ implemented from scratch
- **Optimizations and programming model:**
  - OpenMP (Algorithm parallelism)
  - OpenMP (Data parallelism)
  - MPI+OpenMP+Slurm (Hybrid)
- **Platform:** Google Cloud (Virtual Instance, Cluster with Slurm)

Optimization 1: OpenMP - Algorithm parallelism

```
For cell_img in all images
{
```

Step 0: Input image

Step 1: Pixel intensity histogram



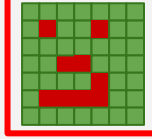
Parallelism using OpenMP

Step 2: Find threshold

```
0, 0, 0, 0, 0, 0, 0,
60,
87,
130, 130, 130, 130, 130, 130…
200, 200, 200
```

Parallelism using OpenMP

Step 3: Final segmentation



Parallelism using OpenMP

```
}
```

Optimization 1: OpenMP - Algorithm parallelism

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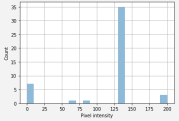

Parallelism using OpenMP

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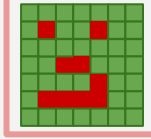
Parallelism using OpenMP

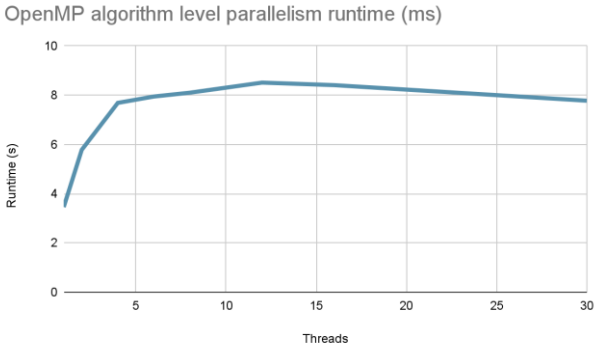
Step 3: Final segmentation



Parallelism using OpenMP

```
}
```

Threads	Runtime (s)	Speedup compared to 1 thread
1	3.456	1
2	5.779	0.59799
4	7.687	0.4496
6	7.945	0.4359
8	8.101	0.4266
12	8.510	0.40614
16	8.407	0.4111
30	7.775	0.4445



Google Cloud: Compute optimized VM with 30 vCPUs.

Optimization 1: OpenMP - Algorithm parallelism

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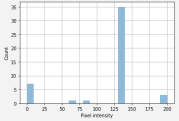
Step 1: Pixel intensity histogram



Parallelism using OpenMP

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Parallelism using OpenMP

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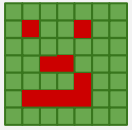

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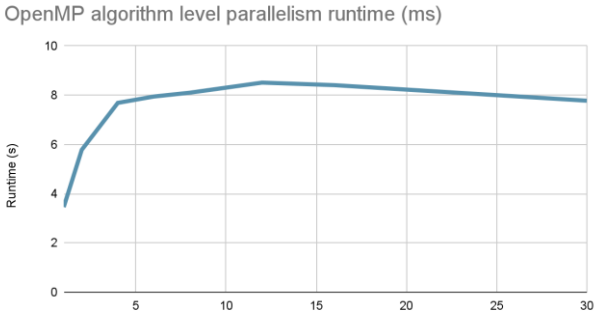

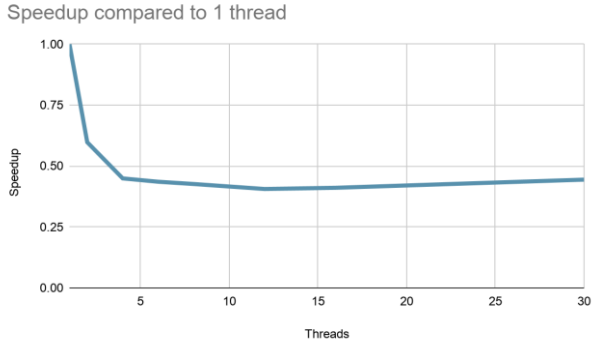

Google Cloud: Compute optimized VM with 30 vCPUs.

Optimization 1: OpenMP - Algorithm parallelism

```
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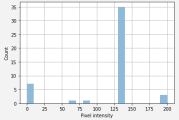
Step 0: Input image

Step 1: Pixel intensity histogram



Parallelism using OpenMP

Step 2: Find threshold

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130, 130, 130, 130, 130, 130…
200, 200, 200
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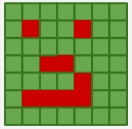
Parallelism using OpenMP

Step 3: Final segmentation



Parallelism using OpenMP

```
}
```

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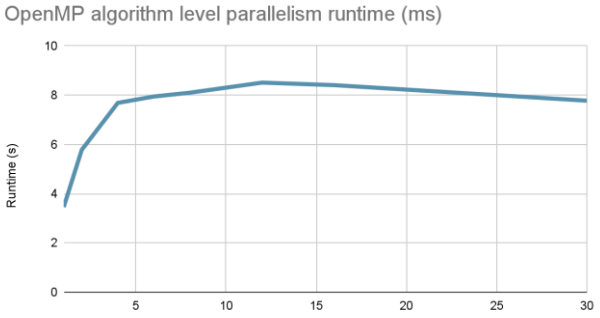
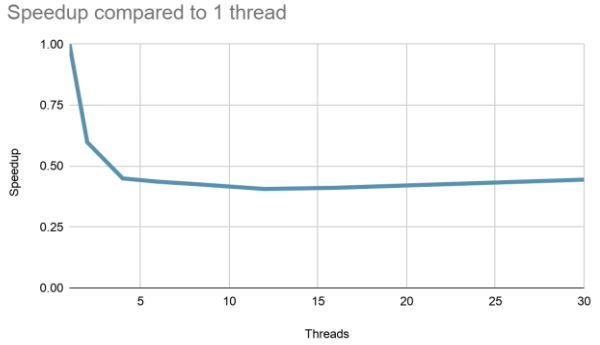




Amdahl's law theoretical max speedup 1.58.

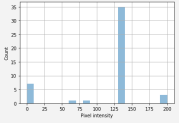
Since each of these parallelized subparts of not compute intensive, the overhead immediately dominates.

Optimization 2: OpenMP - Data parallelism

```
For cell_img in all images
{
```

Step 0: Input image

Step 1: Pixel intensity histogram



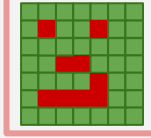
Parallelism using OpenMP

Step 2: Find threshold

```
0, 0, 0, 0, 0, 0, 0,
60,
87,
130, 130, 130, 130, 130, 130…
200, 200, 200
```

Parallelism using OpenMP

Step 3: Final segmentation



Parallelism using OpenMP

```
}
```

 # pragma states before the for loop

Allowing multiple cell images to be simultaneously segmented.

Optimization 2: OpenMP - Data parallelism

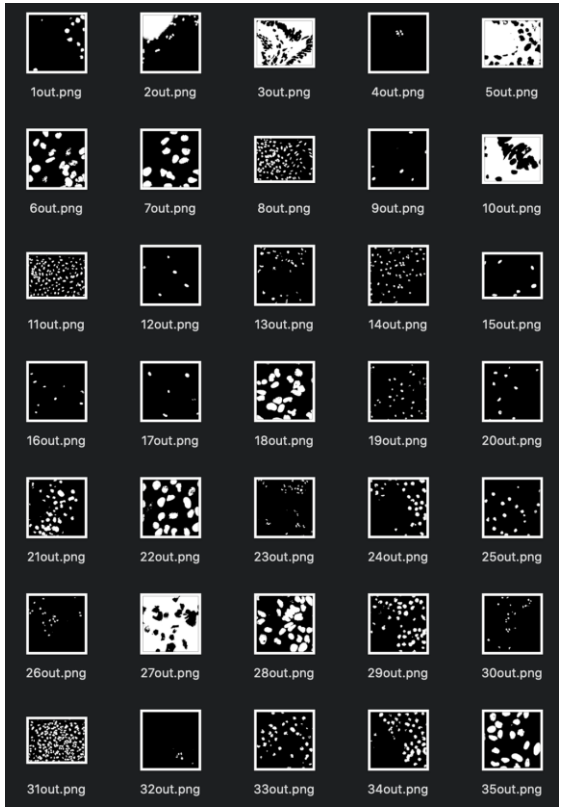
Thread number	Total time(ms)	Speedup of current compared to previous	Speedup of current compared to 1 thread	Step 0: data loading (%)	Step 1: compute histogram (%)	Step 2: finding threshold (%)	Step 3: final segmentation (%)	Step 4: data save (%)
1	3.574s	NA	1	0.46368	0.208419	0.440318	0.19899	0.08334
2	1.794759	1.9915	1.9915	0.471731	0.219885	0.0152618	0.205544	0.0870849
4	0.976506s	1.8379	3.6602	0.473829	0.215001	0.0153819	0.206288	0.0890124
6	0.702265s	1.3905	5.0896	0.471621	0.216026	0.0152663	0.207052	0.089535
8	0.618021s	1.13631	5.7835	0.464095	0.222237	0.0157273	0.208233	0.089284
12	0.539055s	1.14648	6.6307	0.450517	0.218754	0.0158821	0.219383	0.0947447
16	0.442824s	1.2173	8.0716	0.454073	0.218009	0.0157286	0.215558	0.0959675
30	0.387223s	1.1436	**9.2306**	0.536978	0.180146	0.0124914	0.181916	0.0880761
60	0.393248s	0.9847	9.0892	0.760144	0.0795287	0.00555554	0.0804626	0.0733615
90	0.424771s	0.9258	8.4147	0.808752	0.0474346	0.0032952	0.0478846	0.0925408

Optimization 3: MPI + OpenMP + Slurm on GCP

- **Google Cloud Cluster:**
  - 8 nodes
  - Each with 4 vCPUs
  - With SLURM
- **Hybrid Model:**
  - MPI
  - OpenMP
- **Parallel Types:**
  - Data parallelism
  - Algorithm parallelism
- **Best speedup:**
  - **5.096**

node\thread	1 threads	2 threads	4 threads	8 threads
1 nodes	**6.570s**	5.490s	4.785s	4.594s
2 nodes	3.292s	2.709s	2.525s	2.557s
4 nodes	2.211s	1.726s	1.880s	1.848s
6 nodes	1.628s	1.435s	1.403s	1.389s
8 nodes	1.432s	1.369s	1.320s	**1.289s**

Results


1out.png
2out.png
3out.png
4out.png
5out.png
6out.png
7out.png
8out.png
9out.png
10out.png
11out.png
12out.png
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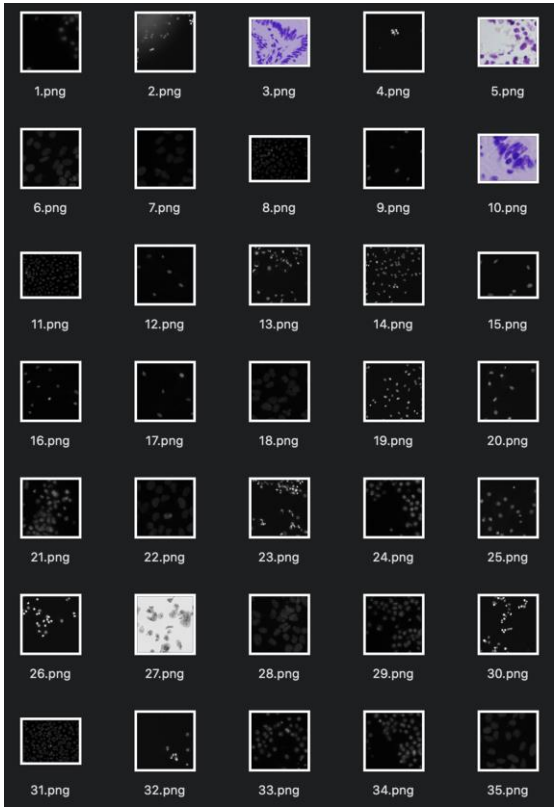
32out.png
33out.png
34out.png
35out.png


1.png
2.png
3.png
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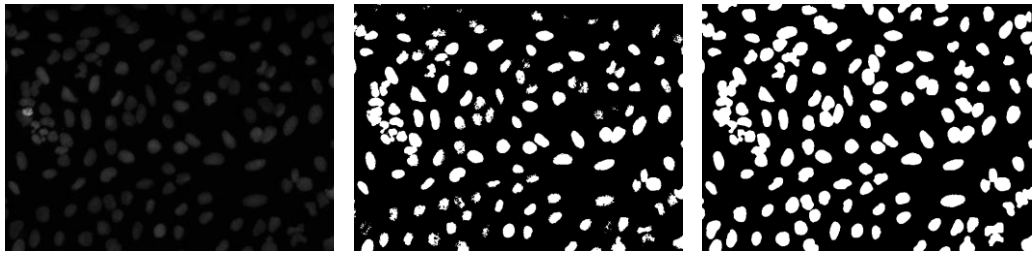
34.png
35.png

Results and Discussion

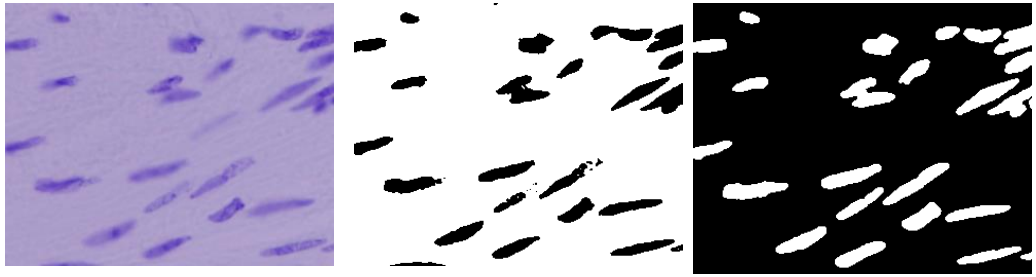
Example 1:

Original image | Otsu's result | Ground truth



Example 2:

Original image | Otsu's result | Ground truth

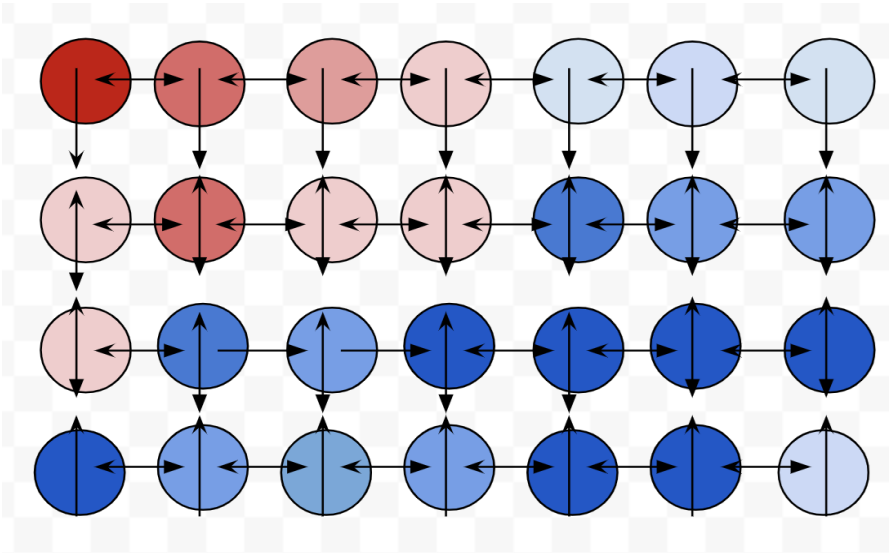


- **Speed:**
  - Extremely fast in speed
  - Great speed up with a maximum of **9.23**
- **Accuracy:**
  - Performs well in most cell segmentations with pixel intensity contrast
- **Pros:**
  - Fast and mostly accurate
  - Little dependency
  - Doesn't need training
- **Cons:**
  - Unable to differentiate foreground and background
- **Not compute intensive:** fast, but not friendly for parallelism

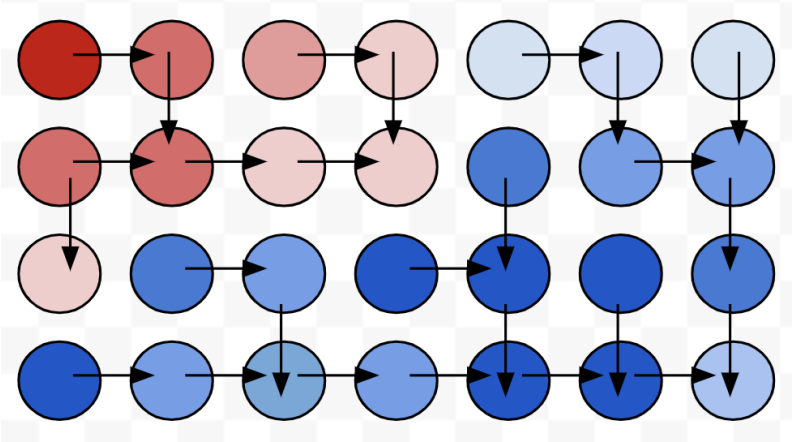
02

Boruvka's method

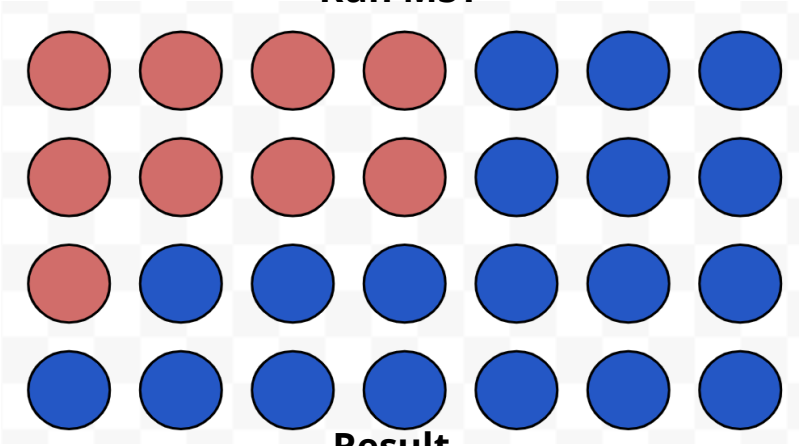
Algorithm



Initialize



Run MST



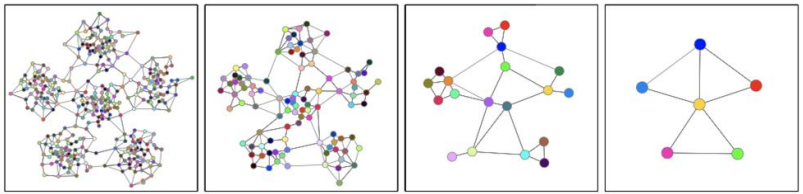
Result

Optimization 1: Memory

Overheads: Storing Graph

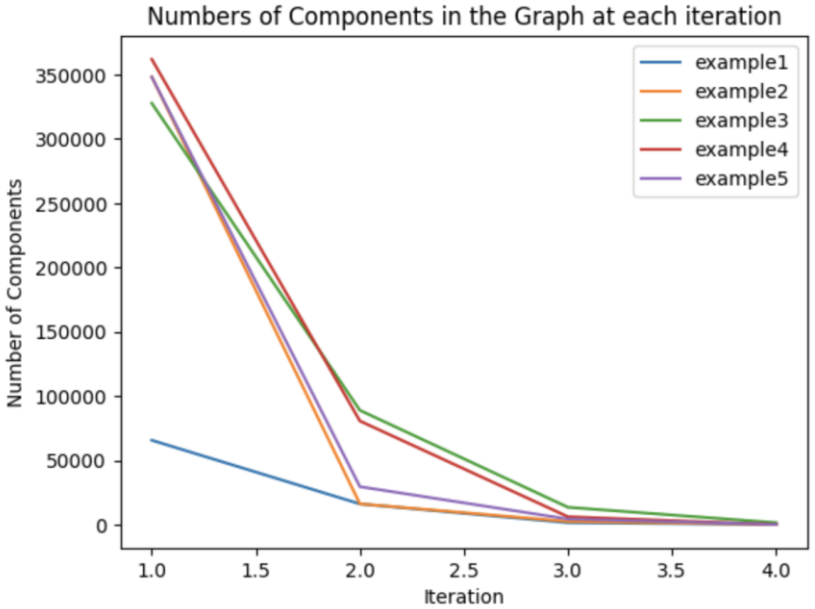
3.5 hours

per 256*256 images



Solution

- Edge compaction



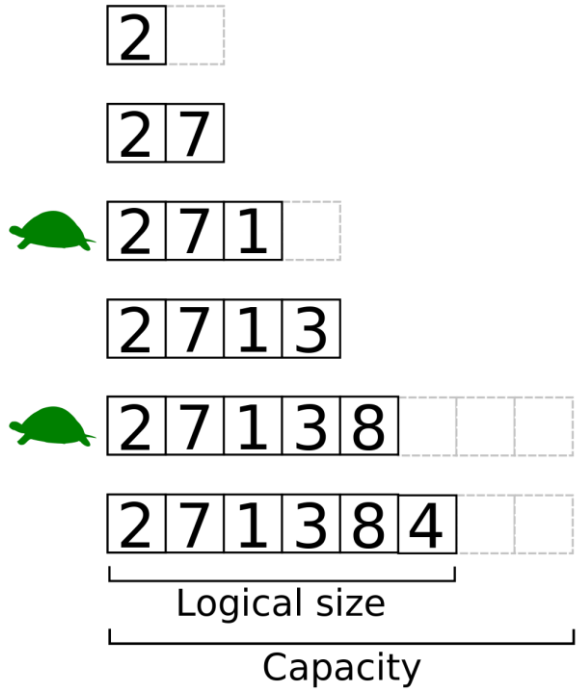
Optimization 1: Memory

Solution (cont.)

- Passed by reference, NOT pass by value!

  (Note: In C++, things are passed by value unless you specify otherwise)

- C++ dynamic memory allocation & deallocation, e.g. malloc(), calloc(), free() delete[] ...



C++'s std::vector: dynamic array

Optimization 1: Memory

Solution (cont.)

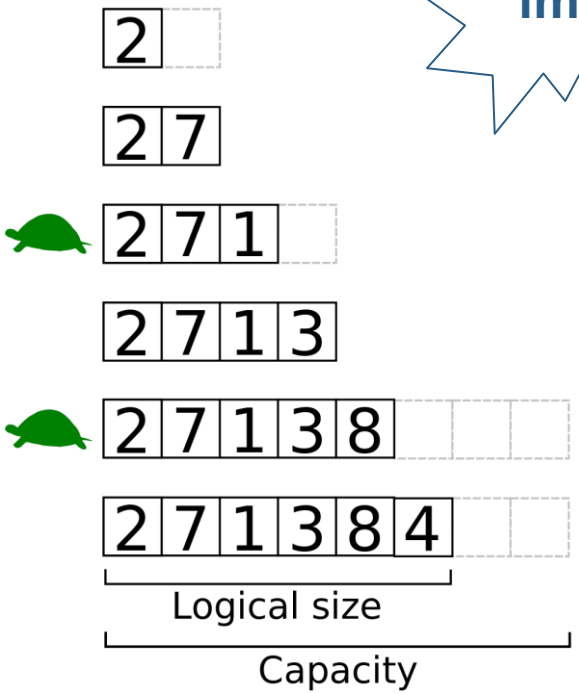
2.96s per image

Don't write code like this!

```
std::vector<int> nums;
for(int i=0; i<n; i++){
    nums.push_back(1);
}
```

Instead,

```
std::vector<int> nums(n,1);
```



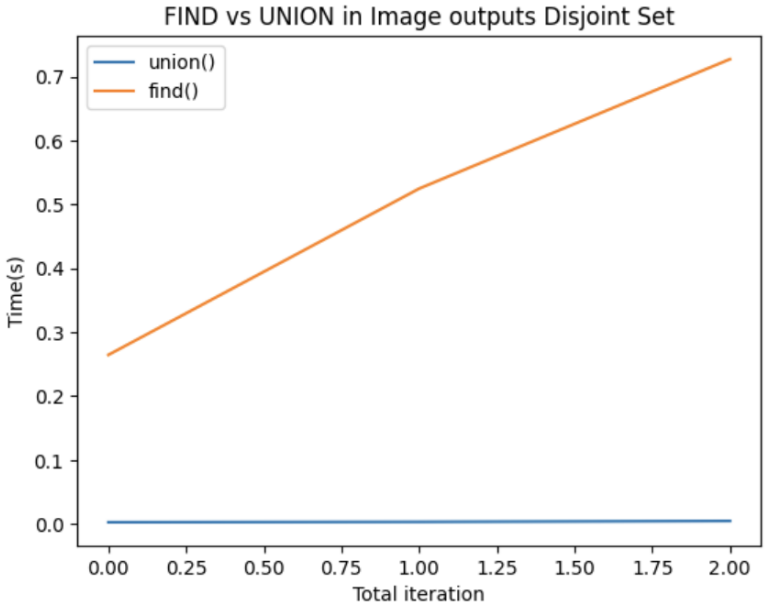
C++'s std::vector: dynamic array

Optimization 2: OpenMP

Total

9m 30s

Now, it takes 2.96s per image! But processing all the images still takes 33m7.4s!



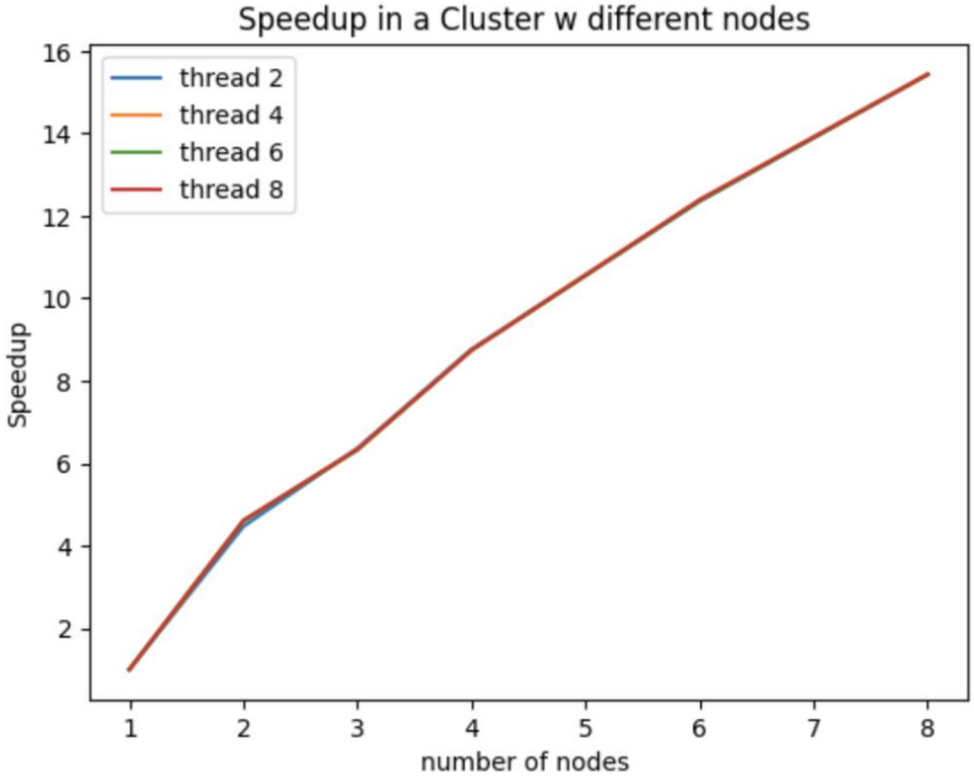
Parallelize find() operation

- OpenMP, #pragma omp parallel for schedule(dynamic)

Overhead: Data Dependency

- C++ built-in function for atomic memory access: __sync_bool_compare_and_swap

Optimization 3: MPI & OpenMP



1 node 8 thread/node, 30vCPU

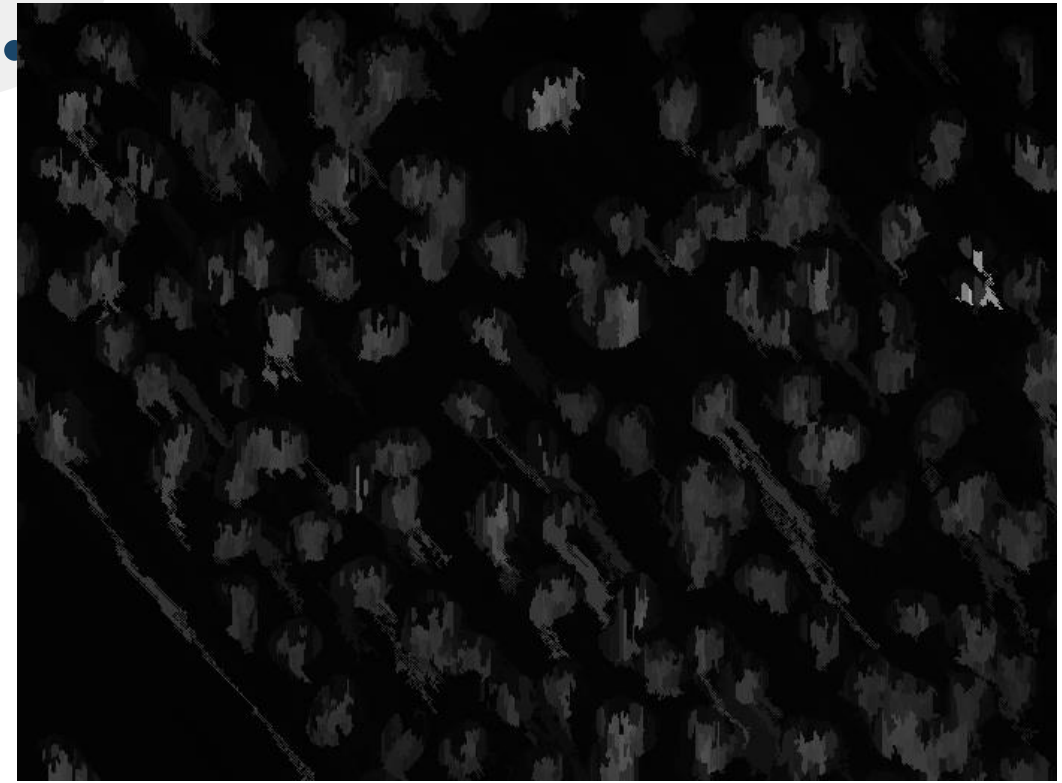
9m 30s

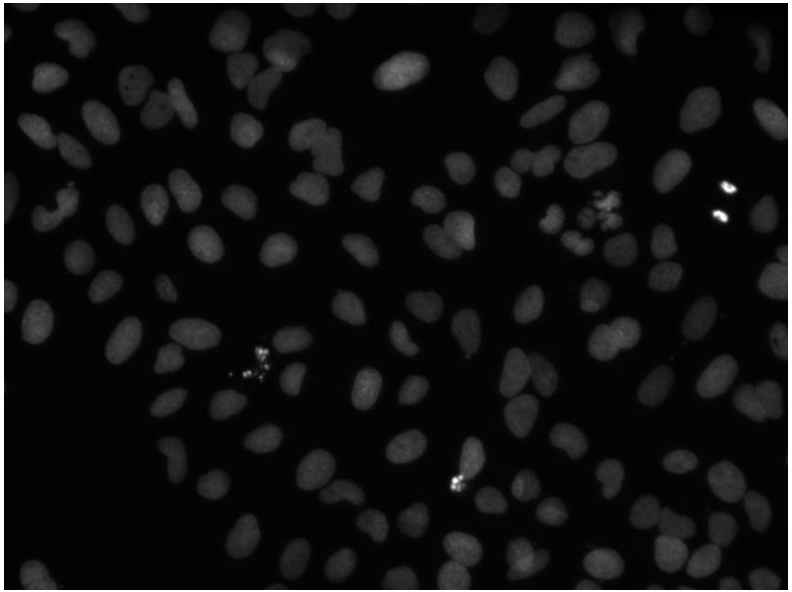
Data Parallelism

8 nodes 4 threads/node, 4vCPU

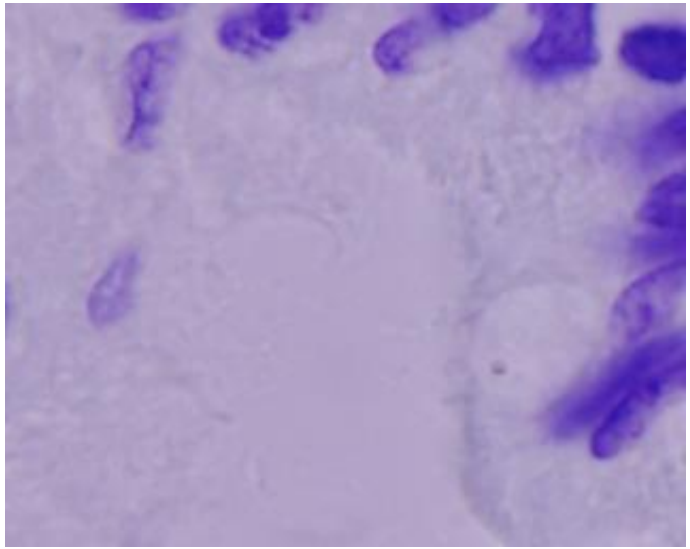
2m 8.79s

Good Results





Bad

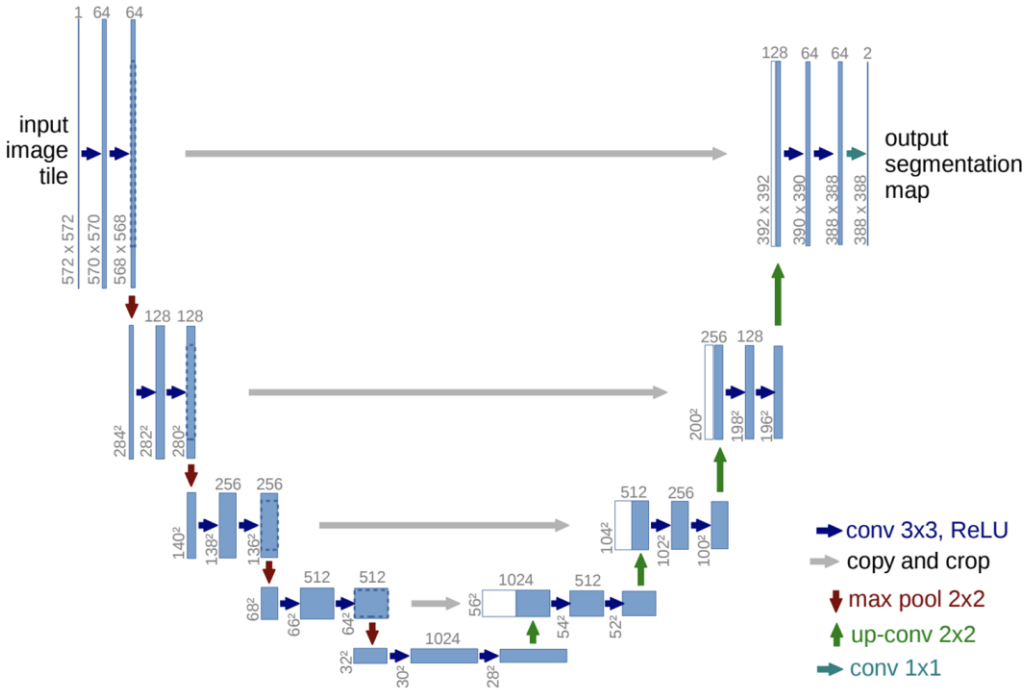


Boruvka: When there is a big color difference, it can do great!

03

UNet

UNet: Model Overview



Convolutional Neural Network

- Highly non-linear function mapping each pixel to 0 or 1
- Huge amount of model parameters

```
Total params: 1,941,105
Trainable params: 1,941,105
Non-trainable params: 0
```

- Learns fast with data augmentation

UNet

Programming Model and Platform

GPU accelerated computing

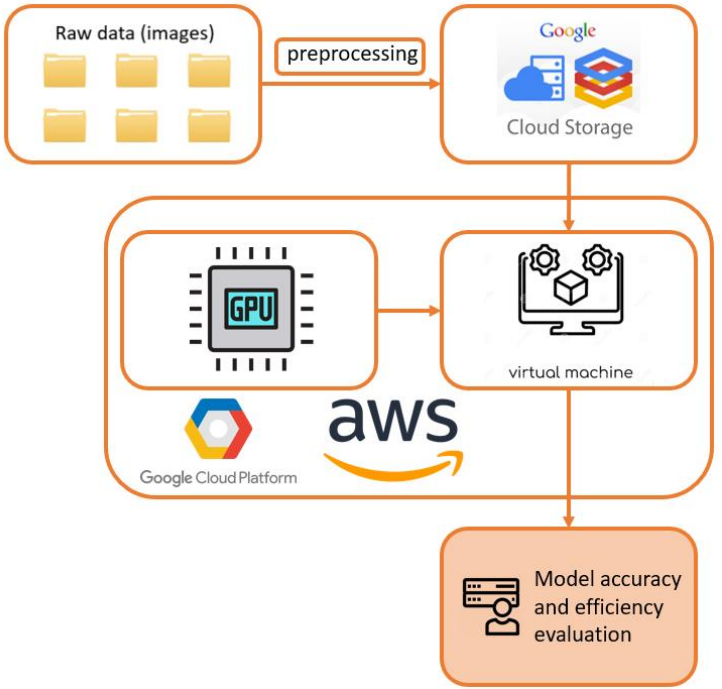
- Single GPU of different types
- Parallel data augmentation and training

Software:

- Python3
- Keras + Tensorflow

Platform:

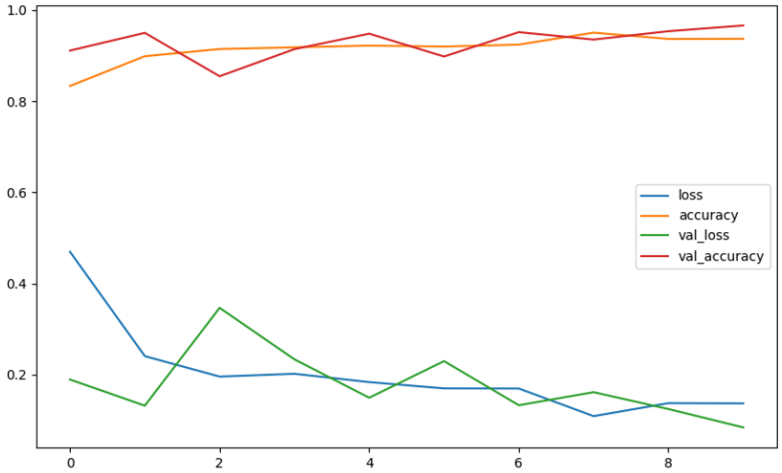
- Google Cloud Platform (GCP)
- AWS



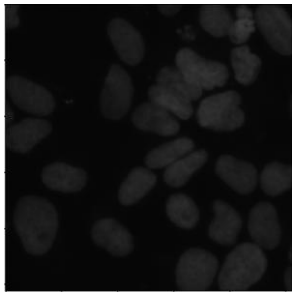
Segmentation Results

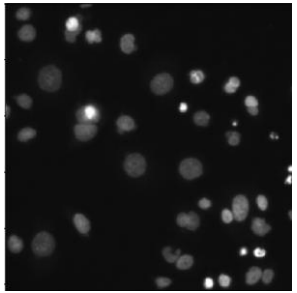
Final pixel classification accuracy: 95%

Learning curve (batch size = 1)

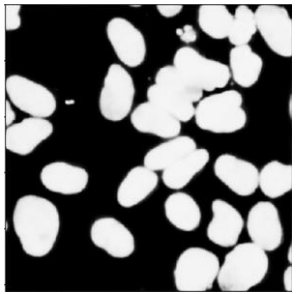


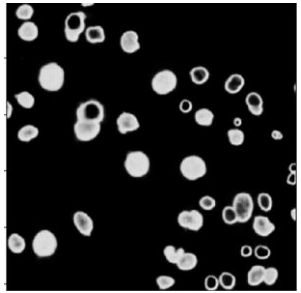
Input Image





UNet Output





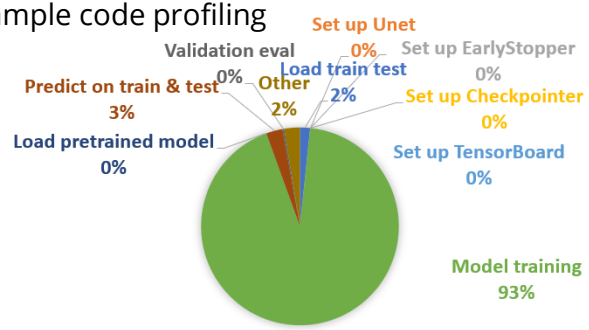
GPU Acceleration

Six VMs (including the baseline)

Instance		GCP c2-standard-30	AWS g3.4xlarge	AWS p2.xlarge	AWS p3.2xlarge	AWS g4dn.4xlarge	GCP n1-standard-16
GPU info	Type	N/A	Tesla M60	Tesla K80	Tesla V100 SXM2	Tesla T4	Tesla P4
	Memory	N/A	7618MiB	11441MiB	16160MiB	15109MiB	7611MiB
	Count	0	1	1	1	1	1
CPU info	Type	Intel(R) Xeon(R) CPU	Intel(R) Xeon(R) Platinum 8259CL @2.50GHz	Intel(R) Xeon(R) E5-2686 v4 @2.30GHz	Intel(R) Xeon(R) E5-2686 v4 @2.30GHz	Intel(R) Xeon(R) Platinum 8259CL @ 2.50GHz	Intel(R) Xeon(R) CPU @2.30GHz
	Count	30	16	4	8	16	16
	Thread(s)/core	2	2	2	2	2	2
	Core(s)/socket	15	8	2	4	8	8
	Socket(s)	1	1	1	1	1	1
	Memory	120 GiB	122 GiB	61 GiB	61 GiB	64 GiB	64 GiB
Price (instance only)		$1.5660/hr	$1.14/hr	$0.90/hr	$3.06/hr	$1.204/hr	$1.376944/hr
Batchsize = 1 Training speed		138s/epoch 696ms/step	14s/epoch 68ms/step	30s/epoch 152ms/step	14s/epoch 70ms/step	12s/epoch 60ms/step	13s/epoch 67ms/step

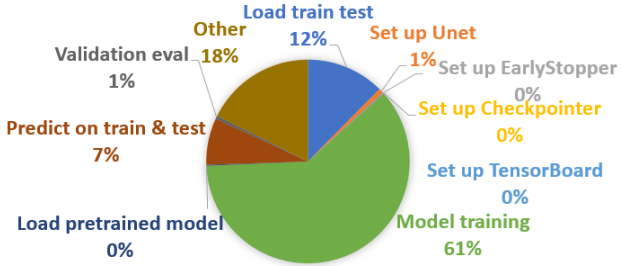
* Much more detailed report can be found in the write-up.

Sample code profiling



BASELINE RUNTIME BREAKDOWN

Script total time: 1521.629 sec

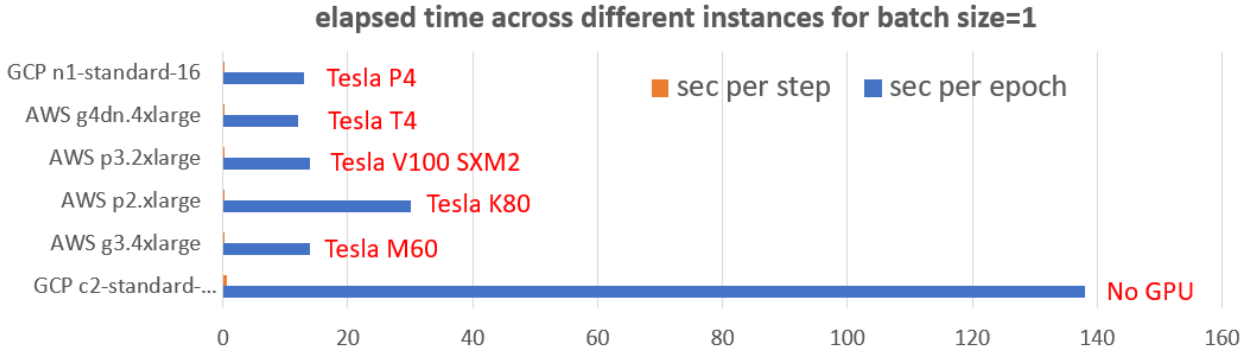


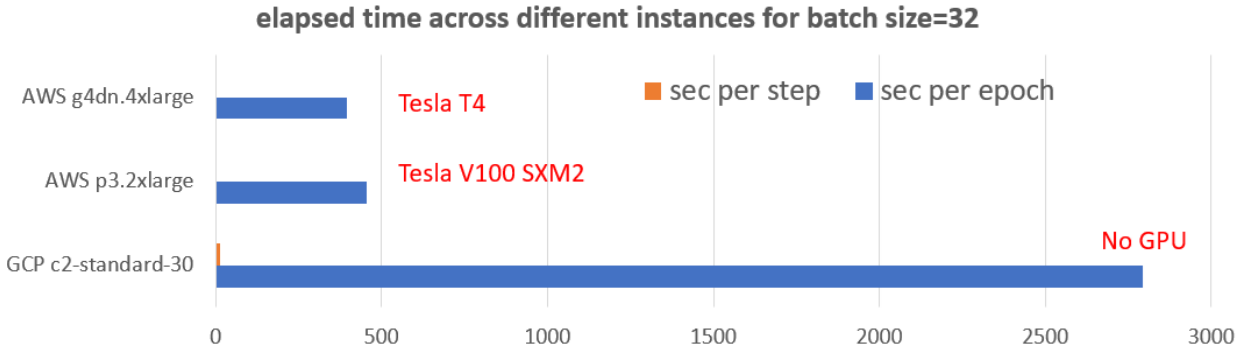
GCP GPU RUNTIME BREAKDOWN

Script total time: 245.146 sec

* Also used cProfile, TensorBoard. Please refer to the write-up.

Speedup and Scalability



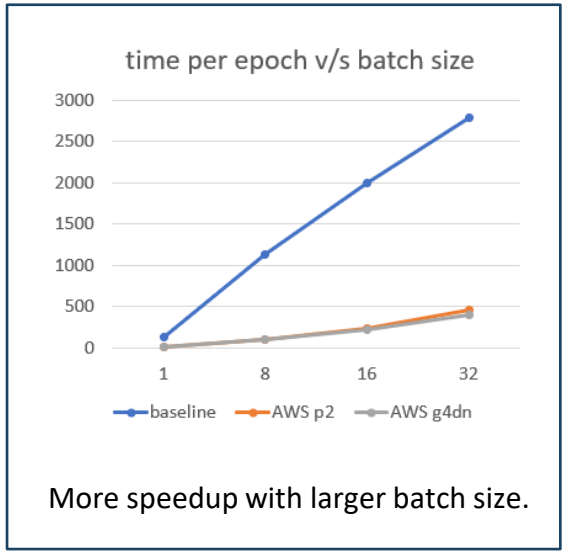


Best speedup: AWS g4dn.4xlarge

~ 11 for batch size = 1

~ 7 for batch size = 32

* compared to baseline

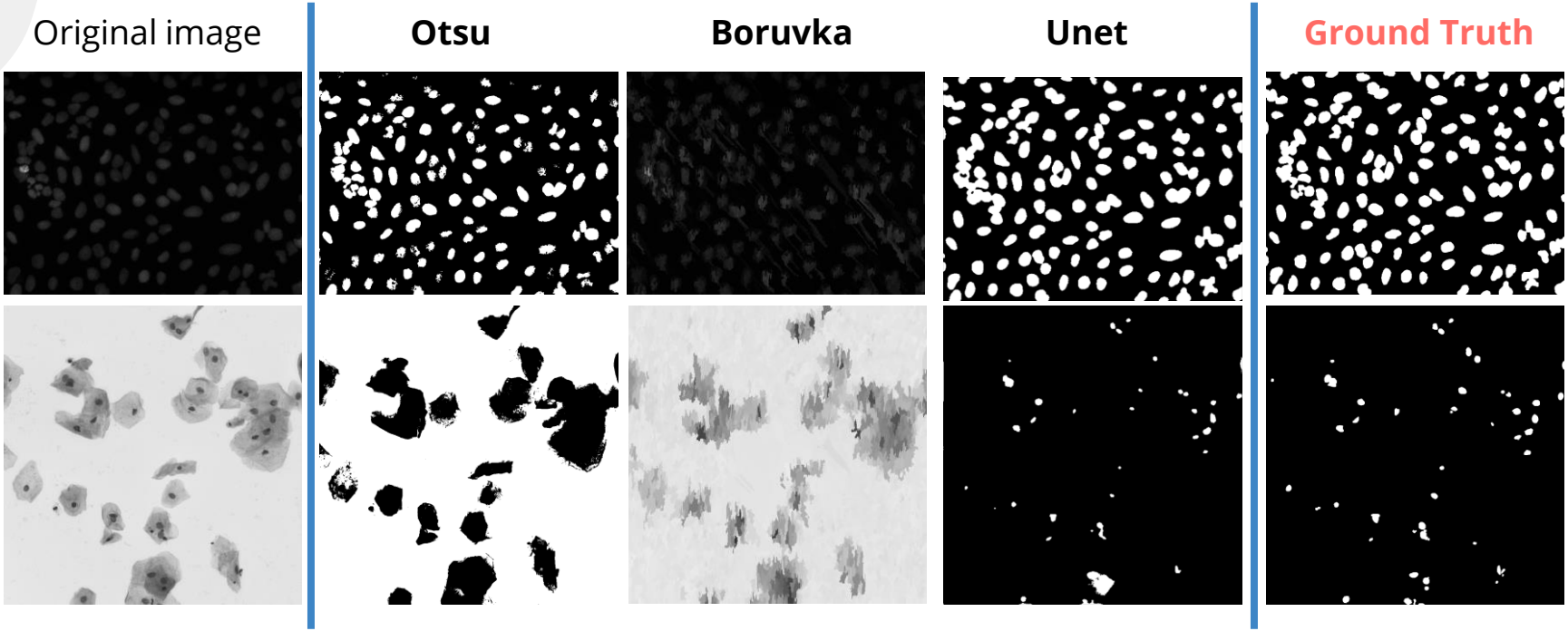


More speedup with larger batch size.

04

Final Recap

Key Results Recap



Levels of Parallelism/Cloud Infra Used

Otsu's / Boruvka's Algorithm

Optimization:
- MPI
- OpenMP

Cloud infrastructure:
- Google Cloud VM
- Google Cloud Cluster

Service:
- Slurm

Levels of Parallelism:
- Task level
- Procedure level
- Loop level

Types of Parallelism:
- Inter node: Data
- Intra node: Function

Language: C++

UNet

Optimization:
- GPU
- Spark

Cloud infrastructure:
- Google Cloud VM + GPU
- AWS VM + GPU

Service:
- Google Cloud Dataproc Cluster

Levels of Parallelism:
- Task level

Types of Parallelism:
- Data parallelism

Language: Python3

Future Work

In addition to the significant speedup of our optimized implementations, we can further leverage

- Multi-GPU instances
- Split huge images for parallel processing

Thank you for watching!

Special thanks to **Haipeng** for discussion and suggestions