ANALYZING REAL-TIME MULTIMEDIA CONTENT FROM NETWORK CAMERAS USING CPUS AND GPUS IN THE CLOUD

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ABSTRACT

Millions of network cameras are streaming real-time multimedia content (images or videos) for various environments (e.g., highways and malls) and can be used for a variety of applications. Analyzing the content from many network cameras requires significant amounts of computing resources. Cloud vendors offer resources in the form of cloud instances with different capabilities and hourly costs. Some instances include GPUs that can accelerate analysis programs. Doing so incurs additional monetary cost because instances with GPUs are more expensive. It is a challenging problem to reduce the overall monetary cost of using the cloud to analyze the real-time multimedia content from network cameras while meeting the desired analysis frame rates. This paper describes a cloud resource manager that solves this problem by estimating the resource requirements of executing analysis programs using CPU or GPU, formulating the resource allocation problem as a multiple-choice vector bin packing problem, and solving it using an existing algorithm. The experiments show that the manager can reduce up to 61% of the cost compared with other allocation strategies.

Index Terms— Resource Allocation, Cloud Computing, Computer Vision, GPGPU, Network Cameras

1. INTRODUCTION

Deployment of network cameras has been growing rapidly in recent years. Network cameras stream real-time multimedia content (images or videos) that can be used for a variety of applications, for example, surveillance, entertainment, and traffic monitoring as shown in Figure 1(a-c). Analyzing the multimedia content from network cameras in real-time may also help first responders. Figure 1(d) shows an image from a camera during the Houston flood of April 2016. Such multimedia content can be used to assess the severity of situations in different locations and to quickly respond to emergencies.

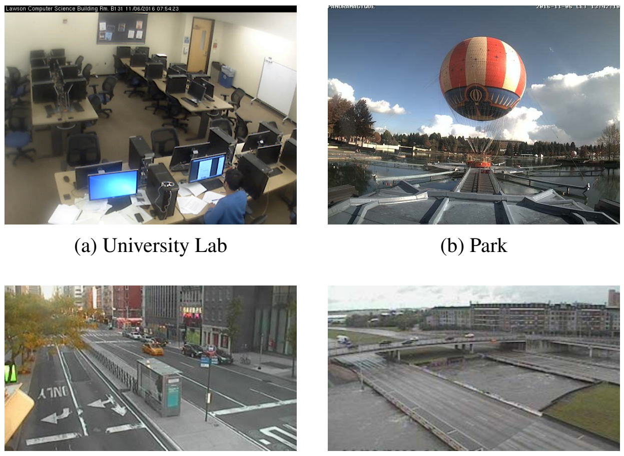

(a) University Lab (b) Park
(c) Street Traffic (d) Houston Flood

Fig. 1: Images from network cameras.

Analyzing the multimedia content from many network cameras requires a significant number of distributed computing resources. Using the cloud can be beneficial because: (i) Cloud vendors use a pay-as-you-go pricing model. That means that users pay only when resources are used. This may reduce the overall monetary cost if the analysis is needed occasionally (e.g., during emergencies). (ii) Cloud vendors offer a variety of cloud instances with different capabilities and hourly costs. Some instances include GPUs. Using GPUs can accelerate analysis programs and achieve higher frame rates. This incurs additional monetary cost because GPU instances are more expensive. This variety makes it a challenging problem to meet the desired frame rates at the lowest possible cost. This paper aims at solving this problem by introducing a resource manager that uses the GPU to achieve higher frame rates and considers both GPU and non-GPU instances to reduce the overall cost. The manager conducts test runs to estimate the resource requirements of analysis programs.

The manager formulates the resource allocation problem as a multiple-choice vector bin packing problem to decide what instance types to use, how many instances to allocate, which data streams to assign to which instances, and which CPU or GPU to analyze the data streams.

To evaluate the manager, the experiments use two programs using convolutional neural networks (VGG-16 [1] and ZF [2]) to detect objects (e.g., persons) in images. The experiments show that the manager can use the GPU to achieve speedup of around 13 (or 16) for VGG-16 (or ZF) and also reduce the cost. This paper has the following contributions:

- It describes a resource manager that reduces the monetary cost of using cloud to analyze real-time multimedia content from network cameras while meeting the desired analysis frame rates.
- The manager uses GPU to achieve higher frame rates and considers both GPU and non-GPU instances to reduce the overall cost.
- The manager considers several factors while allocating resources: (i) the resource requirements of executing analysis programs on either the CPU or the GPU, (ii) the desired frame rates, (iii) the sizes of the frames provided by the cameras, and (iv) the types and costs of both the GPU and non-GPU instances.
- The manager formulates the resource allocation problem as a multiple-choice vector bin packing problem and solves it using an existing algorithm. The experiments show that the manager is able to reduce 61% of the cost compared with other allocation strategies.

2. RELATED WORK

The visual data from many network cameras is publicly available through many sources, such as Departments of Transportation (e.g., `http://www.ohgo.com/`). This data can be used for many applications, such as weather detection [3] and surveillance [4]. Several systems have been developed for analyzing the visual data from cameras, such as IBM Smart Surveillance System [5] and CAM^2 [6].

Zhu et al. [7] explained the advantages of using cloud for multimedia applications. Kaseb et al. [8] proposed a resource manager to reduce the cost of analyzing the data from cameras, but do not consider GPU resources. GPUs can be used to accelerate general purpose computation, such as image processing and computer vision [9]. Different studies used GPUs for face detection [10], motion estimation [11], body tracking [12], etc. This paper considers using GPUs to accelerate and reduce the monetary cost of analyzing the real-time multimedia content from network cameras using the cloud.

3. THE CLOUD RESOURCE MANAGER

The resource manager aims at meeting the performance requirements (i.e., meeting the desired frame rates) at the lowest possible monetary cost. The performance of analyzing a single data stream is defined as the ratio between the actual analysis frame rate and the desired frame rate. The overall performance of the system is then defined as the average performance for all the data streams. The manager aims at maintaining the overall performance above 90%. Our experiments show that this can be achieved by maintaining the utilization of all the resources below 90%. The performance decreases if the resources are overutilized. There is a clear trade-off between meeting the performance requirements and reducing the cost. Allocating fewer instances than necessary decreases the performance, while allocating more increases the cost. Figure 2 shows the main factors affecting resource allocation decisions as well as the resource allocation goals. Section 3.1 discusses the factors considered by the resource manager. Section 3.2 explains how the manager makes resource allocation decisions to achieve its goals.

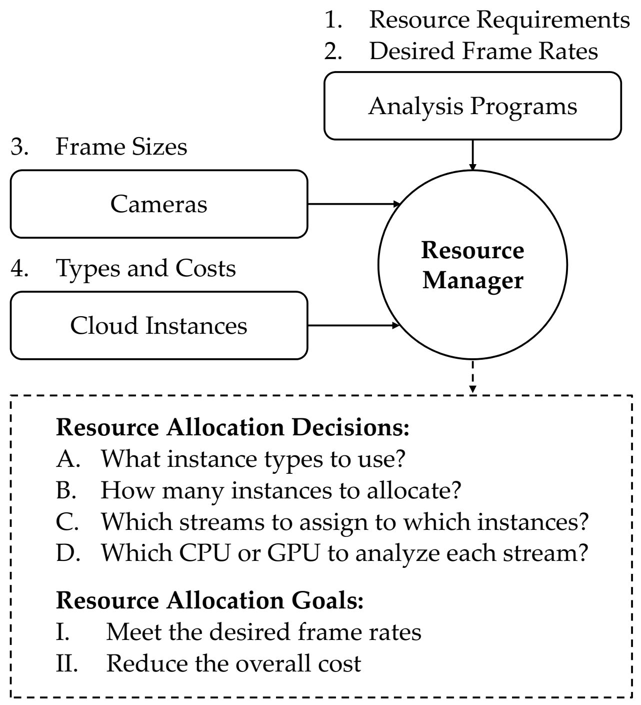

1. Resource Requirements
2. Desired Frame Rates
Analysis Programs
3. Frame Sizes
Cameras
4. Types and Costs
Cloud Instances
Resource Manager
Resource Allocation Decisions:
A. What instance types to use?
B. How many instances to allocate?
C. Which streams to assign to which instances?
D. Which CPU or GPU to analyze each stream?
Resource Allocation Goals:
I. Meet the desired frame rates
II. Reduce the overall cost

Fig. 2: The main factors (1-4) affecting resource allocation decisions (A-D) and the resource allocation goals (I and II).

3.1. Factors Affecting Resource Allocation Decisions

The resource manager considers the following factors while making allocation decisions:

1. Resource Requirements: The manager considers the following types of resources: CPU, memory, GPU, and GPU memory. Different analysis programs require different amounts of resources. For example, some programs are memory intensive while others are CPU intensive. Moreover, some programs have implementations using GPU to achieve higher frame rates. The resource requirements of these programs

Table 1: The capabilities and the hourly costs of some Amazon EC2 instance types with and without GPUs (at Oregon).

Instance	Cores	Memory (GB)	GPUs	Cost
c4.2xlarge	8	15	-	\$0.419
c4.8xlarge	36	60	-	\$1.675
g2.2xlarge	8	15	1	\$0.650
g2.8xlarge	32	60	4	\$2.600

change according to which implementation is used (i.e., CPU or GPU). The resource manager is designed to be used for a variety of applications. Hence, it does not assume any prior knowledge about the analysis programs' resource requirements. The manager conducts two test runs (one using the CPU and the other using the GPU) to estimate the resource requirements of each program by monitoring the utilization of resources while executing the program. The test runs are conducted once and the estimations of the resource requirements can be used for future executions of the same program.

2. Desired Frame Rates: The frame rate at which an analysis program is executed significantly affects its resource requirements. Experiments show that the CPU and GPU requirements of an analysis program increase linearly with its frame rate. Using this linear relationship, the manager can estimate the resource requirements of an analysis program at different frame rates using a single test run conducted at a particular frame rate. In addition, the frame rate may affect different types of resources differently. For example, increasing the frame rate may increase its CPU requirement, but may have no effect on its memory requirement. This causes some analysis programs to be CPU intensive at high frame rates while being memory intensive at low frame rates.

3. Frame Sizes: Different cameras provide streams with different frame sizes (e.g., 640×480). Higher frame sizes require higher resource requirements. The effect of the frame size on the resource requirements of an analysis program depends on the time complexity and the space complexity of the program. Since the resource manager assumes no prior knowledge about analysis programs, the manager repeats the test runs for each unique frame size. Fortunately, there are only a few common frame sizes among network cameras.

4. Types and Costs of Cloud Instances: Cloud vendors offer many instances with different capabilities and hourly costs. Table 1 shows the capabilities and hourly costs of some Amazon EC2 instance types with and without GPUs. The table shows that GPU instances (i.e., g2.2xlarge and g2.8xlarge) are more expensive than non-GPU instances (i.e., c2.2xlarge and c2.8xlarge). The manager decides the types and number of instances needed to meet the desired frame rates at the lowest possible cost.

3.2. Multiple-Choice Vector Bin Packing

To make the resource allocation decisions shown in Figure 2, this paper formulates resource allocation as a multiple-choice

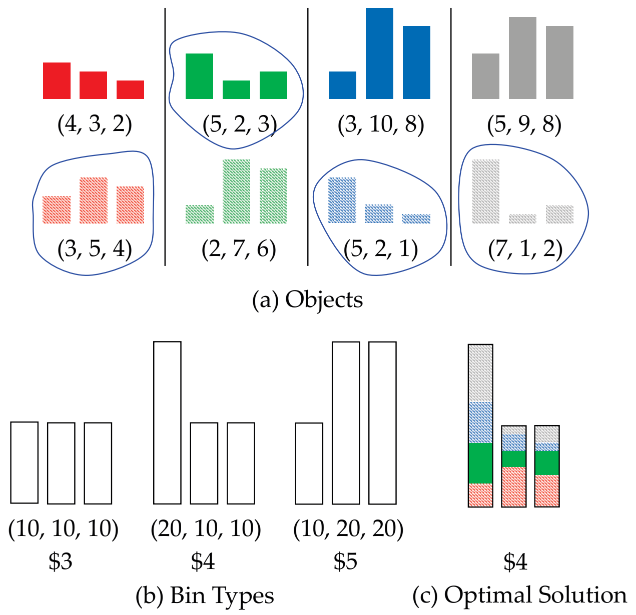
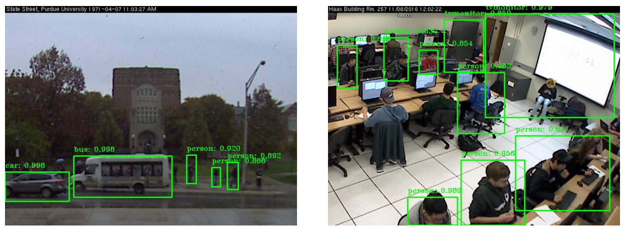


Fig. 3: An example of a multiple-choice 3D bin packing problem with: (a) four objects, each with two possible sizes (b) three bin types (c) the optimal solution using one bin containing all the four objects. This paper uses the algorithm proposed by Brandao and Pedroso [13] to solve the multiple-choice vector bin packing problem.

vector bin packing problem. In this problem [13], a bin has a cost and a multidimensional size. An object may have one of several possible sizes (multiple choices). The goal is to pack all the objects into bins such that: (i) One size is selected for each object. (ii) The overall cost of the used bins is minimized. (iii) The total size of the objects in each bin does not exceed its size in any dimension. Figure 3 shows an example of a multiple-choice 3D bin packing problem.

Similarly, in the resource allocation problem, each instance has an hourly cost and a vector representing its resource capabilities (i.e., CPU, memory, GPU, and GPU memory). For example, the vector $[8, 15, 0, 0]$ represents a non-GPU instance with 8 CPU cores, 15 GB of memory, and no GPUs (e.g., c4.2xlarge). The vector $[8, 15, 1536, 4]$ represents a GPU-instance instance with 8 CPU cores, 15 GB of memory, and a single GPU with 1536 cores and 4 GB of memory (e.g., g2.2xlarge). Each data stream may have one of two possible resource requirements depending on whether it is executed by the CPU or the GPU. For example, the resource requirements of a program may be represented by the vector $[4, 0.75, 0, 0]$ or $[0.8, 0.45, 153.6, 0.28]$ if the program is executed by the CPU or the GPU respectively. This means that if c4.2xlarge executes this program, the CPU utilization would be 50% (i.e., 4/8). If g2.2xlarge executes this program using the GPU, the CPU utilization would drop to 10% (i.e., 0.8/8) and the GPU utilization would be 10% (i.e., 153.6/1536). The goal is to assign all the streams to instances such that: (i) One



(a) VGG-16 (b) ZF

Fig. 4: Sample output results from two network cameras. The objects detected are persons, cars, buses, and monitors.

resource requirement is selected for each stream. This implies deciding if the stream is analyzed by the CPU or the GPU. (ii) The overall cost of all the instances is minimized. (iii) The total resource requirements of all the streams in each instance do not exceed the instance's capabilities for any resource type.

If instances with multiple GPUs (e.g., g2.8xlarge) are available, the dimensions and the multiple-choices of the problem change accordingly. For example, the vector $[8, 15, 1536, 4, 1536, 4, \ 1536, 4, 1536, 4]$ represents an instance with 8 CPU cores, 15 GB of memory, and 4 GPUs each with 1536 cores and 4 GB of memory (e.g., g2.8xlarge). In this case, the vector $[8, 15, 0, 0, 0, 0, 0, 0, 0, 0]$ represents an instance with 8 CPU cores, 15 GB of memory, and no GPUs (e.g., c4.2xlarge). Each data stream may have one of 5 possible resource requirements depending on whether it is executed by the CPU or one of the 4 GPUs. In general, the dimension of the problem is $2 + 2 \times N$ where N is the maximum number of GPUs in an instance. That is because there are 2 resource types (i.e., CPU and memory) for the instance and 2 more resource types (i.e., GPU and GPU memory) for each added GPU. The number of choices for the resource requirements of each stream is $1 + N$ because the stream can be analyzed either by the CPU or by one of the N GPUs.

To solve the multiple-choice vector bin packing, the manager uses the exact method proposed by Brandao and Pedroso [13] and provided through VPSolver (Vector Packing Solver, `http://vpsolver.dcc.fc.up.pt/`). The output of the solver is the types and numbers of bins, which objects are assigned to each bin, and the selected size of each object. In the resource allocation problem, this maps to the types and numbers of instances, which streams are assigned to each instance, and the selected resource requirement of each stream (i.e., which CPU or GPU to analyze the stream). This output precisely represents the resource allocation decisions.

4. EXPERIMENTS AND RESULTS

4.1. Experimental Setup

The experiments use two programs using convolutional neural networks (VGG-16 [1] and ZF [2]) to detect objects (e.g., persons) in images. The experiments use the Python implementation of the region proposal network proposed by Ren et al. [14] to reduce the execution time of VGG-16 and ZF. Figure 4 shows sample outputs. All the experiments analyze 640×480 MJPEG streams from network cameras.

The experiments use a machine with an 8-core Intel Xeon E5-2623 v3 CPU and 32GB of memory. The machine has an NVIDIA K40 GPU with a 12GB of memory. The experiments refer to the machine as a *non-GPU instance* (or a *GPU instance*) when the GPU is not used (or used) respectively. The same pricing of the c4.2xlarge and g2.2xlarge instances (Table 1) is used. The resource manager is generic and can be used with different cloud vendors with the appropriate changes in instance capabilities and hourly costs. The experiments focus on the CPU and GPU utilization because the analysis programs are compute intensive, but the resource manager is generic and considers other resource types (e.g., memory and GPU memory).

Table 2: The effect of using the GPU on the maximum achievable frame rates.

Program	Frame Rate (FPS)		Speedup
	Using CPU	Using GPU	
VGG-16	0.28	3.61	12.89
ZF	0.56	9.15	16.34

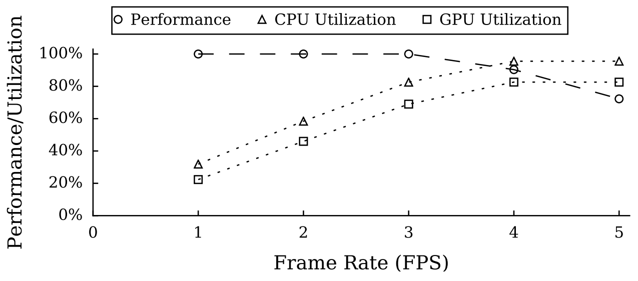


Fig. 5: The effect of the desired frame rate on the resource requirements of VGG-16 as well as the analysis performance.

4.2. Speedup Using GPU

The main goal of the resource manager is to meet the desired frame rates of the analysis programs. Using GPU allows the manager to accelerate the programs to achieve higher frame rates. Table 2 shows the effect of using the GPU on the maximum achievable frame rates of different analysis programs. This shows that the manager can use the GPU to achieve a speedup of around 13 (or 16) for VGG-16 (or ZF).

4.3. Factors Affecting Resource Allocation Decisions

Desired frame rates significantly affect the resource requirements of analysis programs as well as the performance. Fig-

Table 3: The CPU and GPU requirements of VGG-16 and ZF if executed at 0.2 FPS using the CPU or the GPU.

Program	Using CPU		Using GPU	
	CPU	GPU	CPU	GPU
VGG-16	39.4%	-	5.3%	4.6%
ZF	17.8%	-	2.2%	1.2%

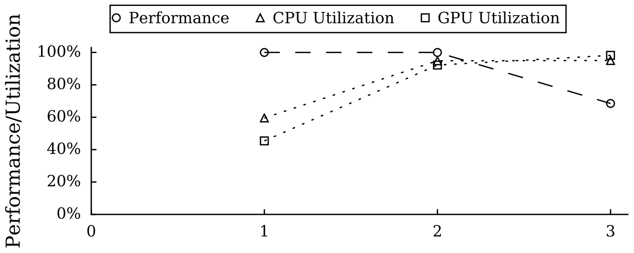


Fig. 6: The effect of the number of data streams being analyzed (using VGG-16 at 2 FPS) on the resource utilization as well as the analysis performance.

ure 5 shows this effect by executing VGG-16 using the GPU at different frame rates. The figure shows that the CPU and GPU utilization increase linearly with the frame rate and the performance is 100%. The performance starts to drop gradually after the CPU resources get overutilized. Since the resource manager aims at maintaining the analysis performance above 90%, the manager attempts to allocate cloud instances such that no resource utilization is above 90%.

Table 3 shows the CPU and GPU requirements of VGG-16 and ZF if executed at 0.2 FPS using the CPU or the GPU. For each program, there are two choices of resource requirements depending on whether it is executed by the CPU or the GPU. The manager estimates these resource requirements for different frame rates based on a test run conducted at a particular frame rate and the linear relationship between the frame rate and the CPU and GPU utilization shown in Figure 5.

The number of streams being analyzed using an instance affects its resource utilization and the performance. Figure 6 shows this by using the GPU to execute VGG-16 at 2 FPS on the streams from multiple cameras. The figure shows that the CPU and GPU utilization increase almost linearly with the number of cameras and the performance is 100%. The performance drops after the CPU and GPU get overutilized.

4.4. Evaluation of Resource Allocation

To evaluate the allocation strategy of the manager described in this paper, we compare it with two different strategies as shown in Table 4. All the strategies benefit from the ability of the manager to estimate the resource requirements of different analysis programs, to formulate the problem as a multiple-choice vector bin packing problem, and to solve it. For ST1 (or ST2), there is a single choice for the resource requirements of each program because only non-GPU (or GPU) instances are considered. The manager described in this paper uses ST3 which considers both non-GPU and GPU instances, hence, two choices of resource requirements exist for each program.

Table 4: The strategies used to evaluate resource allocation.

Abbr.	Resource Allocation Strategy
ST1	Always use non-GPU instances
ST2	Always use GPU instances
ST3	**This Paper:** Use non-GPU and GPU instances to reduce the overall cost of the instances

Table 5: The scenarios used to compare allocation strategies.

Scenario	Program	Frame Rate	Cameras
1	VGG-16	0.25	1
	ZF	0.55	3
2	VGG-16	0.20	1
	ZF	0.50	1
3	VGG-16	0.20	2
	ZF	8.00	10

Table 6: The types and numbers of instances determined by different allocation strategies to handle different scenarios.

Scen.	Strategy	Instances		Hourly	Cost
		non-GPU	GPU	Cost	Savings
1	ST1	4	-	$1.676	0%
	ST2	-	1	$0.650	61%
	ST3	-	1	$0.650	61%
2	ST1	1	-	$0.419	36%
	ST2	-	1	$0.650	0%
	ST3	1	-	$0.419	36%
3	ST1	Fail	Fail	Fail	Fail
	ST2	-	11	$7.150	0%
	ST3	1	10	$6.919	3%

In order to compare the three strategies, we use the three scenarios described in Table 5. The table shows the programs, frame rates, and the number of data streams being analyzed in each scenario. Table 6 shows the types and numbers of instances determined by each strategy to handle each scenario:

Scenario 1: ST1 uses 4 non-GPU instances to handle the 4 data streams. That is because a single non-GPU instance can handle only one stream due to the high CPU requirement of the programs at these frame rate. ST2 and ST3 use a single

GPU instance to handle all the 4 streams because the CPU requirement is decreased significantly while using the GPU. This saves 61% of the overall hourly cost compared with ST1.

Scenario 2: The CPU and GPU requirements of VGG-16 at 0.2 FPS and ZF at 0.5 FPS are low such that a single instance can handle the two streams at the same time. ST1 and ST3 use a single non-GPU instance and either of them saves 36% of the overall hourly cost compared with ST2 which uses a single GPU instance.

Scenario 3: ST1 fails to execute ZF at 8 FPS since the CPU only can execute ZF at a maximum of 0.56 FPS. ST2 uses 10 GPU instances to handle the 10 data streams of ZF and a single GPU instance to handle both the 2 streams of VGG-16. That is because a single GPU instance can handle only one stream of ZF at 8 FPS due to the high CPU requirement. ST3 considers both GPU and non-GPU instances to reduce the overall hourly cost so it can replace a GPU instance with a non-GPU instance. Hence, ST3 saves 3% of the cost compared with ST2.

These experiments demonstrate that different resource allocation strategies are best in different scenarios according to several factors, such as analysis programs and frame rates. The strategy used by the resource manager described in this paper considers both GPU and non-GPU instances and always has the lowest cost compared with the other strategies.

5. CONCLUSION

This paper describes a resource manager that reduces the monetary cost of using the cloud to analyze real-time multimedia content from network cameras while meeting the desired analysis frame rates. The manager uses GPU to achieve higher frame rates and considers both GPU and non-GPU instances to reduce the overall cost. The manager formulates the resource allocation problem as a multiple-choice vector bin packing problem and solves it using an existing algorithm. The experiments show that the manager can reduce up to 61% of the cost compared with other allocation strategies.

6. ACKNOWLEDGEMENTS

The authors would like to thank the organizations that provide the camera data. A complete list of the data sources is available at `https://www.cam2project.net/ack/`. This project is supported in part by National Science Foundation ACI-1535108, CNS-0958487, and OISE-1427808. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the sponsors.

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