CARMA: Contention-aware Auction-based Resource Management in Architecture

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Abstract—Traditional resource management systems rely on a centralized approach to manage users running on each resource. The centralized resource management system is not scalable for large-scale servers as the number of users running on shared resources is increasing dramatically and the centralized manager may not have enough information about applications' need. In this paper we propose a distributed game-theoretic resource management approach using market auction mechanism to find optimal strategy in a resource competition game. The applications learn through repeated interactions to choose their action on choosing the shared resources. Specifically, we look into two case studies of cache competition game and main processor and co-processor congestion game. We enforce costs for each resource and derive bidding strategy. Accurate evaluation of the proposed approach show that our distributed allocation is scalable and outperforms the static and traditional approaches.

Index Terms—Game Theory, Resource Allocation, Auction.

1 Introduction

The number of cores on chip multiporcessors (*CMP*) is increasing each year and it is believed that only many-core architectures can handle the massive parallel applications. Server-side *CMP*s usually have more than 16 cores and potentially more than hundreds of applications can run on each server. These systems are going to be the future generation of the multi-core processor servers. Applications running on these systems share the same resources like last level cache (*LLC*), interconnection network, memory controllers, off-chip memories, auxiliary processing capability like co-processors etc. Along with rapid growth of core integration, the performance of applications highly depend on the allocation of resources and specially the *contention* for shared resources [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11]. In particular, as the number of co-runners running on the shared resource increase, the magnitude of performance degradation increases. As a result, this new architectural paradigm introduces several new challenges in terms of scalability of resource management and assignment on these large-scale servers. Therefore, a scalable competition method between applications to reach the optimal assignment can significantly improve the performance of co-runners on a shared resource. Figure 1 shows an example of performance degradation for 10 *spec 2006* applications running on a shared 10MB *LLC* and solo run on 1MB *LLC*.

Among these shared resources, sharing *CPU*s and *LLC*s plays an important role in overall CMP utilization and performance. Modern *CMP*s are moving towards heterogeneous architecture designs where one can get advantage of both small number of high performance *CPU*s or higher number of low performance cores. The advent *Intel Xeon Phi* co-processors is an example of such heterogeneous architectures that during run-time the programmer can decide to run any part of the code on small number of *Xeon* processors or higher number of *Xeon Phi* co-processors. Therefore, the burden of making decisions on getting the shared resources is moving towards the applications. In addition to the shared *CPU*s, shared *LLC* keeps data on chip and reduces off-chip communication costs [12]. Sometimes an application may flood on a cache and occupy a large portion of available memory and hurt performance of another application which rarely loads on memory, but its accesses are usually latency-sensitive. Recently, many proposals target partitioning the cache space between applications such that (1) each application gets the minimum required space, so that per-application performance is guaranteed to be at an acceptable level, (2) system performance is improved by deciding how the remaining space should be allocated to each one.

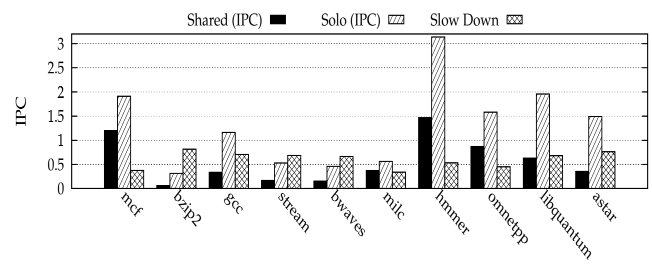

Fig. 1: Performance degradation of 10 different *spec 2006* applications sharing *LLC*.

Prior schemes [3], [12], [13], [14], [15], [16], [17] are marching towards these two goals, usually by trading off the system complexity and maximum system utilization. It is shown that neither a pure private *LLC*, nor a pure shared *LLC*, can provide optimal performance for different workloads [6]. In general, cache partitioning techniques can be divided into way partitioning and co-scheduling techniques. In a set-associative cache, partitioning is done by per-way allocation. For example, in a 512KB 4-Way shared

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TABLE 1: Complexity comparison of state-of-the-art *LLC* partitioning/co-scheduling algorithms.

Algorithm	Search Space
Utility-based main algorithm [13]	$\binom{N+K-1}{N-1}$
Greedy Co-scheduling [17] N applications and N/K caches	$\binom{N}{K}$
Hierarchical perfect matching [17] N applications	N^4
Local optimization [17] N applications and N/K caches	$(N/K)^2\binom{2K}{K}$
CAGE N applications and K resources	$O(NK)$

cache, allocating 128KB capacity to application A means to allow it storing data blocks in only one way per-set, without accessing remaining. Co-scheduling techniques try to co-schedule a set of applications with lowest interference together at the same time such that the magnitude of slow-down for each application is the same or a performance metric is optimized for all applications. However, it is shown that, depending on the objective function for the performance metric, cache allocation can result in totally different allocations [4]. In general Prior schemes have the following three challanges:

1. Scalability: All of the prior schemes suffer from scalability; especially when the approach is tracking the application's dynamism [3], [13], [17]. The reason is that algorithm complexity becomes higher in dynamic approaches. The root cause of this complexity is that all previous techniques make decisions (cache partitioning, co-scheduling) centralized using a central hardware or software. For example, main algorithm of [13] has exponential complexity $O(\binom{N+K-1}{K-1})$ where N is the number of applications sharing *LLC* and K is the number of ways. Table 1 shows the state of the art cache partitioning algorithms and their complexity of checking performance of different permutations.

2. Static-based: Most of the prior works, use static co-scheduling to degrade slow-down of co-running applications on the same shared cache. However, static-based approaches can not catch dynamic behavior of applications. Figure 2 shows an example of two applications' IPC (*hmmer* and *mcf*) from *Spec 2006* under different *LLC* sizes. It is shown that static-based approaches can not capture the dynamism in application's behavior and ultimately degrade the performance a lot.

3. Fairness: Defining a single parameter for fairness is challenging for multiple applications, since applications have different performance benefits from each resource during each phase. In prior works fairness has been defined as a unique metric (eg. IPC, Power, Weighted Speed-up) for all applications. Therefore, in current approaches, the optimization goal of algorithms is the same for all applications. Consequently, we cannot sum up applications that desire different metrics in the same platform to decide on. However, if one application needs better IPC and another requires lower energy, the previous algorithms are not able to model it. The only way to address diversity of metrics (to be optimized) is to have an appropriate translation between different metrics (eg. IPC to Power) that is not trivial, while not addressed in any prior study.

In this paper, we present a distributed heterogeneous resource assignment method to address all the above shortcomings including scalability, dynamism and fairness, while applications can get their desired performance based on their utility functions:

1. Decentralized: Dual of each centralized problem is decentralized, if optimization goal is broken into a smaller meaningful sub-problems. In the context of heterogeneous resource assignment this is straightforward; which decision on resource portion given to an application is done by itself while competes with others for best assignment. To achieve this, we introduce a novel market-based approach. Roughly speaking, the complexity of our approach in worst case scenario (for each application) is $O(NK)$ where N is the number of applications and K is the number of arcs in the resources available to each applications. However, on average the auction terminates in less than $N/2$ iterations.

2. Dynamic: In order to confront the scalability problem of previous approaches we use a market-based approach to move the decision making to the individual applications. Iterative auctions have been designed to solve non-trivial resource allocation problems with low complexity cost in government sale of resources, *eBay*, real estate sales and stock market. Similarly, decentralized computation complexity is definitely lower than centralized (for each application) which provides the opportunity to make the decision (revisiting the allocation) in small time quantum (or when a new applications leaves or comes into the system).

3. Fair: The proposed method solves heterogeneous resource assignment problem in the context of marketing. Applications' demand regardless of the global optimization objective (IPC, Power, etc.) translates to virtual tokens (bids, coins, etc.) and these tokens are used for resource assignment; making it local optimization objectives. Hence, resource assignment can be performed for different applications with different objectives known as utility functions.

Overall, the proposed approach for cache contention game on average brings in 33.6% improvement in system performance (when running 16 applications) compared to shared *LLC*; while reaching less than 11.1% of the maximum achievable performance in the best dynamic scheme and for heterogeneous core case study, it brings in 106.6% improvement (when running 16 applications at the same time). In addition, the performance improvement increases even more as the number of co-running applications increase in the system.

Other potentials: The two case studies of cache partition-

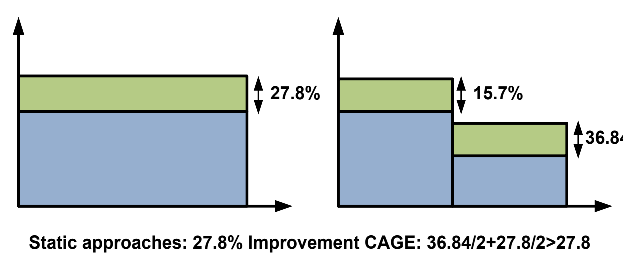

Fig. 2: Performance comparison of static and dynamic scheduling of two applications (*hmmer* and *mcf* from *Spec 2006*) under two different *LLC* sizes.

ing and CPU sharing is an example for resource partition and the proposed method can be employed in any other resource partitioning.

We introduce a distributed game-theoretic cache partitioning approach for different applications in large scale resource competition games. In short, we pay for a high-end CMP system for servers and guarantee that each application/user takes its best from the system.

The reminder of the paper is organized as follows. Section 2 discusses the background and motivation behind this work. In section 3 we discuss our auction based game model. Section 4 discusses the case study of cache contention game and the case study of main processor and co-processor contention and simulation results. Section 5 studies related works and Section 6 concludes the paper with a summary.

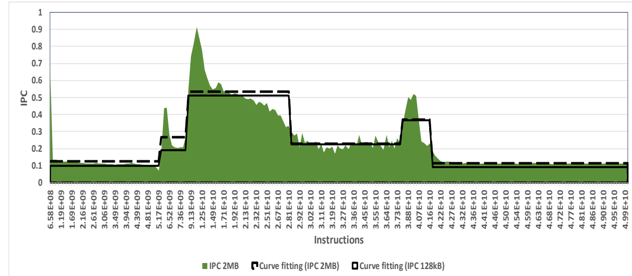

Fig. 3: Phase transition in mcf with different L2 cache sizes.

2 Motivation and Background

2.1 Motivation

Different applications have different resource constraint with respect to CPU, memory, and bandwidth usage. Having a single resource manager for all existing resources and users in the system result in inefficiencies since it is not scalable and the operating system may not have enough information about application's needs. For example, traditional LRU-based cache strategy uses cache utilization as a metric to give larger cache size to the applications which have higher utilization and lower cache size to the applications with lower cache utilization. However more cache utilization does not always result in better performance. Streaming applications for example have very high cache utilization, but very small cache reuse. In fact, the streaming applications only need a small cache space to buffer the streaming data. With rapid improvements in semiconductor technology, more and more cores are being embedded into a single core and managing large scale application using a single resource manager becomes more challenging.

In addition, defining a single fairness parameter for multiple applications is non-trivial since applications have different bottlenecks and may get different performance benefits from each resources during each phases of its execution time. Defining a single reasonable parameter for fairness is somewhat problematic. For instance, simple assignment algorithms which try to equally distribute the resources between all applications ignores the fact that different applications have different resource constraints. As a consequence, this makes the centralized resource management systems very inefficient in terms of fairness as well as performance needs of applications. We need a decentralized framework, where all applications' performance benefit could be translated into a unique notion of fairness and performance objective (known as utility function in economics) and the algorithm tries to allocate resources based on this translated notion of fairness. This translation has been well defined in economics and marketing, where the diversity of customer needs, makes more economically efficient market [18].

Economists have shown that in an economically efficient market, having diverse resource constraints and letting the customers compete for the resources can make a Nash equilibrium where both the applications and the resource managers can be enriched.

Furthermore, applications' demand changes over time. Most resource allocation schemes pre-allocate the resources without considering the dynamism in applications' need and number of users sharing the same resource over time. Therefore, applications' performance can degrade drastically over time. Figure 3 shows phase transitions for instruction per cycle (IPC) of mcf application from *spec 2006* over 50 billion instructions.

We try to find a game-theoretic distributed resource management approach where the shared hardware resources are exposed to the applications and we will show that running a repeated auction game between different applications which are assumed to be rational, the output of the game would converge to a balanced Nash equilibrium allocation. In addition, we will compare the convergence time of the proposed algorithm in terms of dynamism in the system. We will evaluate our model with two case studies: 1- Private and Shared last level cache problem, where the applications have to decide if they would benefit from a larger cache space which can potentially get more congested or a smaller cache space which is potentially less congested. Based on the number of other applications in the system the application can change its strategy over the time. 2- Heterogeneous processors (*Intel Xeon* and *Xeon Phi*) problem, where we perform experiments to show how congestion affects the performance of different applications running on an *Intel Xeon* or *Xeon Phi* co-processors. Based on the congestion in the system the application can offload the most time consuming part of its code on *Xeon Phi* co-processors or not.

2.2 Background

Game theory has been used extensively in economics, political and social decision making situations [19], [20], [21], [22], [23], [24], [25], [26]. A game is a situation, where the the output of each player not only depends on her own action in the game, but also on the action of other players [27]. Auction games are a class of games which has been used to formulate real world problems of assigning different resources between n users. Auction game framework can model resource competition, where the payoff (cost) of each application in the system is a function of the contention level (number of applications) in the game.

Inspired by market-based interactions in real life games, there exists a repeated interaction between competitors in a resource sharing game. Assuming large number of applications, we show that the system gets to a Nash equilibrium where all applications are happy with their resource assignment and don't want to change their state. Furthermore, we show that the auction model is strategy-proof, such that no application can get more utilization by bidding more or less than the true value of the resource. In this paper we propose a distributed market based approach to enforce cost on each resource in the system and remove the complexity of resource assignment from the central decision maker.

The traditional resource assignment is performed by the operating system or a central hardware to assign fair amount of resources to different applications. However, fair scheduling is not always optimal and solving the optimization problem of assigning m resources between n users in the system is an integer programming which is an NP-hard problem and finding the best assignment problem becomes computationally infeasible. Prior works focus on designing a fair scheduling function that maximizes all application's benefit [28], [29], [30], [31], [32], while applications might have completely different demands and it is not possible to use the same fairness function for all. By shifting decision making to the individual applications, the system becomes scalable and the burden of establishing fairness is removed from the centralized decision maker, since individual applications have to compete for the resources they need. Applications start with the profiling utility functions for each resource and bid for the most profitable resource. During the course of execution time they can update their belief based on the observed performance metrics at each round of the auction. The idea behind updating the utility functions is that the history at each round of decision point shows the state of the game. This state indicates the contention on the current acquired resource. The pay-off function in each round depends on the state of the system and on the action of other applications in the system.

2.2.1 Sequential Auction

Auction-based algorithms are used for maximum weighted perfect matching in a bipartite graph $G = (U, V, E)$ [33], [34], [35]. A vertex $U_i \in U$ is the application in the auction and a vertex $V_j \in V$ is interpreted as a resource. The weight of each edge from U_i to V_j shows the utility of getting that particular resource by U_i. The prices are initially set to zero and will be updated during each iteration of the auction. In sequential auctions, each resource is taken out by the the auctioneer and is sequentially auctioned to the applications, until all the resources are sold out.

2.2.2 Parallel Auction

In a parallel auction, the applications submit their bids for the first most profitable item. The value of the bid at each iteration is computed based on the difference of the highest profitable object and the second highest profitable object. The auctioneer would assign the resources based on the current bids. At each iteration, the valuation of each resource is updated based on the observed information during runtime which shows the contention on that particular resource.

TABLE 2: Notation used in our formulations.

N	Number of applications
K	Number of cache levels
T	Time intervals where the bidding is hold
m	Number of applications which can get a resource
p	Number of phases for each application during its course of execution time
n	Number of applications competing for a specified resource
M	Number of resources
P_i	Number of phases for application i
δ	dynamic factor that shows how much we can rely on the past iterations.
U	The applications which shows the left set of nodes in the bipartite graph.
V	The resources which shows the right set of nodes in the bipartite graph.
E	The edges in the bipartite graph.
$G = (U, V, E)$	A bipartite graph showing the resource allocation between the applications and the set of resources.
$b_{i,k}$	User i's bid for k th resource
B_i	The total budget (sum of bids) a user have
C_k	The total capacity of each resource
p_j	The price of resource $j \in V$ in the auction.
$Bottleneck_{1,i}$	The first bottleneck resource for application i
$Bottleneck_{2,i}$	The second bottleneck resource for application i
$v_{i,m}(T)$	The valuation function of application i for resource m at time T

3 CAGE: A Market-based Contention-aware Game-theoretic resource assignment

3.1 Model Description

Consider n applications and i instances of m different resources. Applications arrive in the system one at a time. The applications have to choose among m resources. There exists a bipartite graph between the matching of the applications and the resources.

In general, there can be more than one application to get a shared resources. However, each application can not get more than one of the available heterogeneous resources. For example, if we have two cache space of 128kB (one way) and 256kB (two ways), the application can either get the 128kB of cache space or 256kB and can't get both of them at the same time. Furthermore, each resource m_i has a cost C_i which is defined by the applications' bid in the auction.

Figure 4 shows auction-based framework to support *CAGE* between N applications that execute together competing for M different resources. Each application has a utility table that shows how much performance it gets from each M resources at each time slot. Based on the utility tables, applications submit bids for the most profitable resource. Based on the submitted bids, the auctioneer decides about the resource assignment for each resource, and updates the prices. Next, the applications who did not get any assignment compete for the next most profitable resource based on the updated prices repeatedly until all applications are assigned. Figure 4 shows an example of a resource assignment and the corresponding bipartite graph.

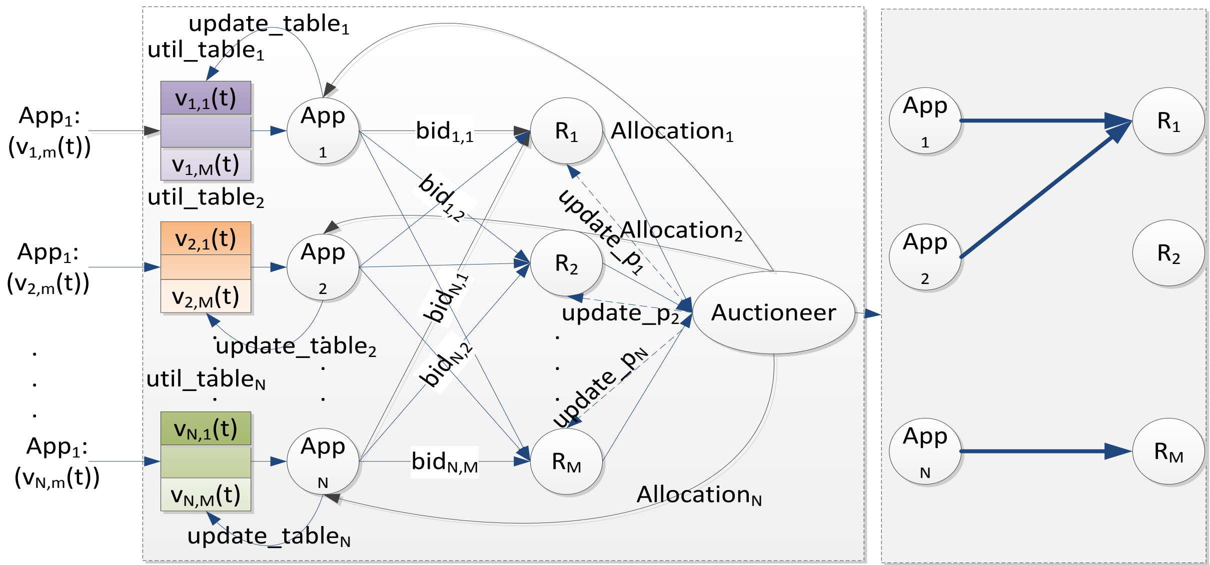

Fig. 4: Framework for auction-based resource assignment (CAGE).

3.2 Problem Defenition

We formulate our problem as an auction based mechanism to enforce cost/value updates for each resource as follows:

- **Valuation $\mathbf{v_{i,m}}$** : Any application has a valuation function which shows how much he benefits from ith resource. The valuation function at time $t = 0$ for cache contention case study is derived from the IPC (instruction per cycle) curves which is found using profiling, and for processor and co-processor contention case study is derived from the profiling solo performance metric of the application. However, in general, each application can choose its own utility function.
- **Observed information**: The observed information at each time step is the performance value of the selected action in the game. Therefore, the applications repeatedly update the history of their valuation function over time.
- **Belief updating**: At each iteration step of the auction, the applications update their valuation of each resource based on the observed performance on each resource. The update at time T is derived using the following formula:

$$v_{i,m}(T) = \frac{\sum_{t=0}^{T} \delta^{T-t} v_{i,m}(t)}{\sum_{t=0}^{T} \delta^{T-t}} \tag{1}$$

Where $v_{i,m}(t)$ shows the observed valuation of resource m at time step t by user i in the system; δ shows the discount factor between 0 and 1 which shows how much a user relies on its past observations in the system. The discount factor is chosen to show the dynamics in the system. If the observed information in the system changes fast, the discount factor is nearly zero which means that we can't rely on the past observations very much. However if the system is more stable and the observed information does not change fast, the discount factor is chosen to be near 1. We choose the discount factor as the absolute value of the correlation coefficient of the observed values of the valuations at each iteration step which is calculated as follows:

$$\delta = \frac{E(v_{i,m})^2}{{\sigma_{v_{i,m}}}^2} \tag{2}$$

- **Action**: At each time step the applications decides which resource to bid and how much to bid for each resource.

Table 2 shows important notation used throughout the paper. In the following sections, we describe our distributed optimization scheme to solve the problem.

3.3 Distributed Optimization Scheme

The goal is to design a repeated auction mechanism which is run by the operating system to guide the applications to choose their best resource allocation strategy. The applications' goal is to maximize their own performance and the operating system wants to maximize the total utility it gains from the applications. Then, each application can use its own utility function and evaluates the resources based on how much it likes that particular resource.

Applications' approach: The application i want to maximize the total utility with respect to a limited budget for all phase p of its execution time.

$$\forall i \in U \quad maximize \quad \sum_{p=1}^{P_i} \sum_{m=1}^{M} v_{i,m,p} - b_{i,m,p},$$
$$subject\ to \quad \sum_{p=1}^{P_i} \sum_{m=1}^{M} b_{i,m,p} \leq B_i. \tag{3}$$

OS's approach: The operating system wants to maximize the social welfare function which is translated into submitted bids from the applications in a limited resource constraints.

$$maximize \quad \sum_{i=1}^{N} \sum_{p=1}^{P_i} \sum_{m=1}^{M} b_{i,m,p} A_{i,m,p},$$
$$subject\ to \quad \sum_{i=1}^{N} \sum_{m=1}^{M} A_{i,m,p} \leq A_{max}, \quad \forall p \in P,$$
$$A_{i,m,p} \in \{0,1\}, \quad \forall i \in U, \ \forall m \in V, \ \forall p \in P. \tag{4}$$

Illustrative example: As an illustrative example, suppose we have two different resources, a large cache of 1MB which can be shared between applications, and two private caches of 512KB which are not shared. There are two applications competing for the cache space. One of the applications wants to minimize its request latency and the other one wants to maximize number of instructions executed per cycle. Suppose that both applications have two phases $(0, T)$ and $(T, 2T)$. Suppose if the first application gets the larger cache space its request latency reduces by 20 percent in first phase and by 40 percent in the second phase. The second application's *IPC* increases by 35 percent in the first phase and by 25 percent in the second phase if it gets the larges cache space. Also, assume they both have 60 tokens (bids) to submit. The first application invests 20 token (bids) for the first phase and 40 tokens for the next phase. He should redistribute the tokens for the next phase if he did not get the resource he wants in the first phase. The second application invests 35 tokens in the first phase and 25 tokens in the next phase. The auctioneer (OS) at each phase decides to allocate which resource to which applications. Since, the social welfare would be maximized if the auctioneer allocates both applications with the larger cache space, they would both get the larger resource. Then the first application notices that its utility function does not improve as he predicts and adjusts the utility table and can either change its allocation or stay on current allocation.

3.4 Analysis

The distributed optimization problem seems complex. However, in reality the problem can be splitted into simpler subproblems since each application knows its bottleneck resource and would first bid for the first bottleneck resource to maximize its utility.

We suppose all applications in the system are risk-neutral which means they have a linear valuation of utility function. Each risk neutral agent wants to maximize its expected revenue. Risk attitude behaviors are defined in [36] where

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Algorithm 1: CAGE: Parallel Auction for heterogeneous resource assignment.

Input: A bipartite Graph (U, V, E).
Output: The allocation of resources to applications.

1 At t=0 the valuation of each application for each resource is derived using profiling while running alone.

2 For each application $U_i \in U$, the first bottleneck resource is

$$Bottleneck_{1,i} = V_{i,m} = arg \max_{m \in V} (v_{i,m} - p_m)$$

Next, find the second bottleneck resource for each applications $U_i \in U$ in the system:

$$Bottleneck_{2,i} = V_{i,k} = arg \max_{k \in V, k \neq m} (v_{i,k} - p_k)$$

3 Each application submits the bid for its first bottleneck resource using the following formula:

$$b_{i,m} = V_m - V_k + p_j + \epsilon$$

Each resource $V_j \in V$, which can be shared between m applications, is assigned to the m highest bidding applications $Winner_j = i_1, i_2, ..., i_m$ and the price for that resource is updated as follows:

$$p_j = arg \max_{i_1, i_2, \ldots, i_m \in U} \sum_{k=1}^{m} (b_{i_k, j})$$

4 The $minBid$ for each resource is updated as the minimum bid of m applications who acquired the resource. That is

$$minBid = arg \min_{i \in Winner_j} (b_{i,j})$$

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the agents can broadly be divided into risk averse, risk seeking and risk neutral. Risk averse agents prefer determinitic values rather than risky value profits and risk seeking applications have a superlinear utility function and prefer risky utilities than sure utilities. Next, we derive the Bayes Nash equilibrium strategy profile for all agents in the system assuming risk neutrality.

Definition 1. A strategy profile a is a pure Nash equilibrium if for every application i and every strategy $a'_i \neq a_i \in A$ we have $u_i(a_i, a_{-i}) \geq u_i(a'_i, a_{-i})$

Theorem 1. Suppose n risk-neutral applications whose valuations are derived uniformly and independently from the interval $[0, 1]$ compete for one resource which can be assigned to m application who have the highest bid in the auction. We will show that Bayes Nash equilibrium bidding strategy for each application in the system is to bid $\frac{n-m}{n-m+1} v_i$ whre v_i is the profit of application i for getting the specified resource.

Theorem 1, states that whenever there is a single resource that users compete to get it with different valuation functions, the Nash equilibrium strategy profile for risk-neutral

TABLE 3: Comparison of *Intel Xeon* and *Xeon Phi* Processors.

Processors	Xeon E5-2680	Xeon Phi SE10P
Cores/Sockets	8/2	61/1
Clock Frequency	2.7 GHz	1.1 GHz
Memory	32GB 8x4G 4-channels DDR3-1600MHz	8GB GDDR5
L1 cache	32 KB	32 KB
L2 cache	256 KB	512 KB
L3 cache	20 MB	-

users is to bid $\frac{n-m}{n-m+1}v_i$. This term tends to the true value of the object when n is a large number.

In case of more than one resource competition we derive Algorithm 1 and will prove that it is Nash equilibrium in the game. The algorithm is inspired by work of Bertsekas [33] that uses an auction for network flow problems. In the first step, all valuations are set to the solo-run of application's performance. Next, each application submits a bid for its first bottleneck resource. The bid should be larger than the price of the object which is intitialized to zero in the begining of the program. The applications only have incentive to bid a value no more than the difference of the first bottleneck and second bottleneck resource. Otherwise, it would submit a smaller bid to the second bottleneck and get the same revenue as paying more for the first bottleneck resource. In order to break the equal valuation function between two different applications, we use ϵ scaling such that at each iteration of the auction the prices should increase by a small number.

4 Case Studies

4.1 CPU Scale-up Scale-out Game

The emerging high performance computing applications lead to the advent of *Intel Xeon Phi* co-processor, that when their highly parallel architecture is fully utilized, can run order of magnitude more performance than the existing processor architectures. The *Xeon Phi* co-processors are the first commercial product of Intel *MIC* processors where the hardware architecture is exposed to the programmer to choose running the code on either *Xeon* processor or *Xeon Phi* co-processors. It is possible that, during the course of execution, either the processor or the co-processor get congested and the performance of the application degrades a lot. Therefore, making a decision to offload the most time consuming part of the program on *Xeon* or *Xeon Phi* should be made online, based on the contention level. In this section we look at the case study of our auction-based model on decision making of running the application on the main or co-processor in a highly congested environment.

The experiment results of this section are run on *Stampede* cluster of *Texas Advanced Computing Center*. Table 3 shows the comparison of *Intel Xeon* and *Xeon Phi* architectures which is used in this section. It is observed that congestion has a significant effect on the performance of running the application on *Xeon* and *Xeon Phi* machines. Since most cloud computing machines are shared between thousands of users, the programmer not only should get benefit of parallelism by offloading the most time consuming part of the code to the larger number of low-performance cores (*Xeon Phi*), but also should consider the congestion level (number of co-runners) in the system. To this end, we performed experiments on *Stampede* clusters. We executed *MiniGhost* application which is a part of *Mantevo* project [37] which uses difference stencils to solve partial differential equations using numerical methods. The applications use the profiling utility functions at $t = 0$ and during course of execution can update the utility function based on the observed performance on each core using Equation 1. Then, they can revisit their previous action on running the code on either the processor or co-processor during run-time.

Figure 5 shows the total execution time with respect to congestion we made in *Xeon* and *Xeon Phi*. In this experiment we ran the same problem size on a *Xeon* and *Xeon Phi* machine multiple times, so that we could see the effect of load on the total execution time of our application. It was observed that with the same number of threads *Xeon*'s performance degrades more than *Xeon phi*. Next, we tried to change the application behavior using congestion-aware game theoretic algorithm to offload the most time consuming part of the application based on the performance behavior of applications. Figure 6 shows the result of our game-theoretic model during the execution time. It is observed that during the course of execution, the applications change their strategy on either choosing the main processor or the co-processor and all applications' performance converge to a equilibrium point where applications don't want to change their strategy.

Furthermore, it is shown that CAGE can bring in up to 106.6% improvement in total execution time of applications compared to static approach when the number of co-runners is six. The performance improvement would be significant when the number of co-runners increase. Figure 7 shows the performance comparison of CAGE and static approach which does not consider the congestion dynamism in the system and the decision is only made based on the parallelism level in the code.

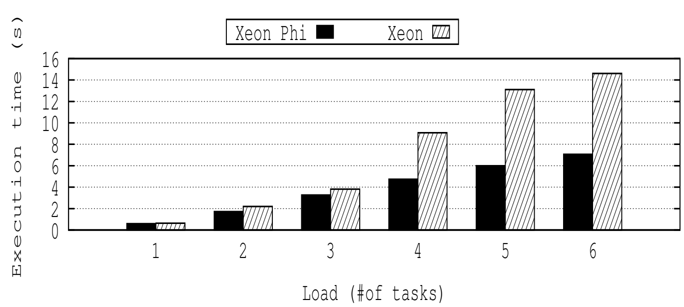


Fig. 5: Congestion effect on *Xeon* and *Xeon Phi* machines.

4.2 A Case Study of Private and shared cache game

One of the challenging problems in *CMP* resource management systems is whether applications benefit from a shared large last level cache or an isolated private cache. We evaluated CAGE performance, on a 10MB LLC shown in Figure 8, where 2MB, 1MB, 512kB, 256kB and 128kB levels of LLC can potentially be shared between 16, 8, 4,

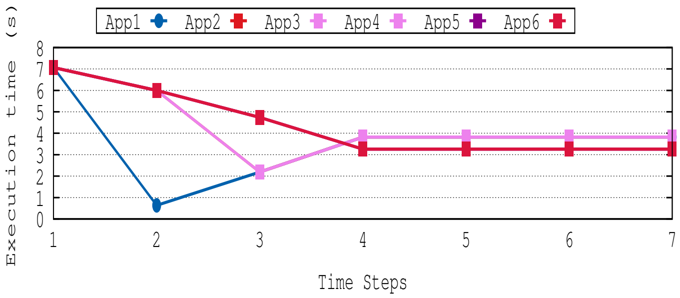


Fig. 6: Performance of 6 instance of applications during time for our proposed game model.

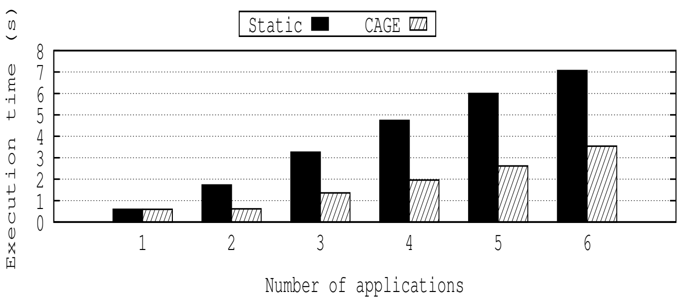


Fig. 7: Performance comparison of congestion-aware schedule versus static schedule.

2 and 1 applications respectively, the cache levels have 16, 8, 4, 2, and 1 ways. Table 5 summarizes the studies workloads and their characteristics, including miss per kilo instructions (*MPKI*), memory bandwidth usage, and IPC. We use applications from *Spec 2006* benchmark suite [38]. We use *Gem5* full system simulator in our experiment [39], [40]. Table 4 shows the experimental setup in our experiments.

To evaluate the performance of our proposed approach we use utility functions for different number of ways shown in Figure 9. These utility functions at the start of the execution can be found using either profiling techniques or stack distance profile [5], [41], [42] of applications assuming there is no co-runners in the system. Next, during run-time the applications can update their utility functions based on Equation 1. Therefore, there is a learning phase where applications learn about the state of the system and update the utilities accordingly. The stack distance profile indicates how many more cache misses will be added if the application has less number of ways in the cache. Based on the stack distance profile, the applications can update their utility function and bid for the next iteration of the auction if they like to change their allocation. Next, we bring an example of the auction for one time step of the game. This time step can be repeated once an application arrives or leaves the system or when an application's phase changes during run-time. However, in case of one application's phase change or arriving or leaving the system, the algorithm reaches the optimal assignment in much fewer iterations since all other assignments are fixed and a few applications would be affected.

Example: As an example, suppose we have 5 different applications and 5 different cache levels with different

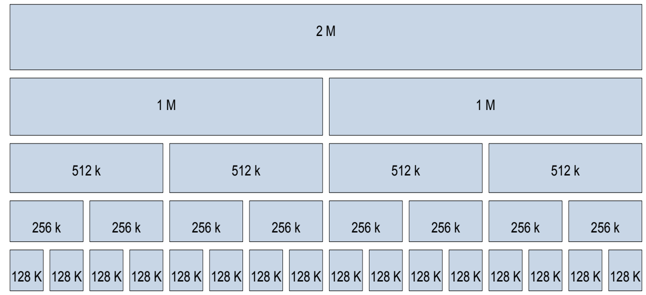


Fig. 8: Our proposed last level cache hierarchy model.

TABLE 4: Experimental Setup.

Processors	Single threaded with private L1 instruction and data caches
Frequency	1GHz
L1 Private ICache	32 kB, 64-byte lines, 4-way associative
L1 Private DCache	32 kB, 64-byte lines, 4-way associative
L2 Shared Cache	128 kb-2 MB, 64-byte lines, 16-way associative
RAM	12 GB

TABLE 5: Evaluated workloads.

#	**Benchmark**	MPKI	Memory BW	IPC
1	astar	1.319	373 MB/s	2.057
2	bwaves	10.47	1715 MB/s	0.661
3	bzip2	3.557	1194 MB/s	1.367
4	dealII	0.935	307 MB/s	2.107
5	GemsFDTD	0.004	2.19 MB/s	2.023
6	hmmer	2.113	1547 MB/s	2.861
7	lbm	19.287	3954 MB/s	0.533
8	leslie3d	8.469	1942 MB/s	1.297
9	libquantum	10.388	1589 MB/s	0.531
10	mcf	16.93	820 MB/s	0.073
11	namd	0.051	20.32 MB/s	2.362
12	omnetpp	10.34	1147 MB/s	0.504
13	sjeng	0.375	139.2 MB/s	1.403
14	soplex	4.672	390.8 MB/s	0.513
15	sphinx3	0.349	202.8 MB/s	2.223
16	streamL	31.682	3619 MB/s	0.581
17	tonto	0.260	107 MB/s	2.036
18	xalancbmk	12.703	1200 MB/s	0.558

capacities of 128KB, 256KB, 512KB, 1MB and 2MB. In addition, suppose the 128kB cache level can not accomodate more than one application and 256kB cache can accomodate 2 applications, 512kB level can have 4 applications, 1MB cache can have 8 applications and 2MB cache can have at most 16 applications. Let's assume the following matrix be the utility function of each application on each cache level.

Some applications may get better utility from smaller cache space since they are less congested and since these applications have low data locality, moving to larger cache spaces not only does not increase their performance but also degrades the performance by evicting other applications from the cache and making contention on the memory bandwidth which is a more vital resource for them [1].

1. *libquantum*, *streamL*, *sphinx3*, *lbm* and *mcf* are examples of such applications.

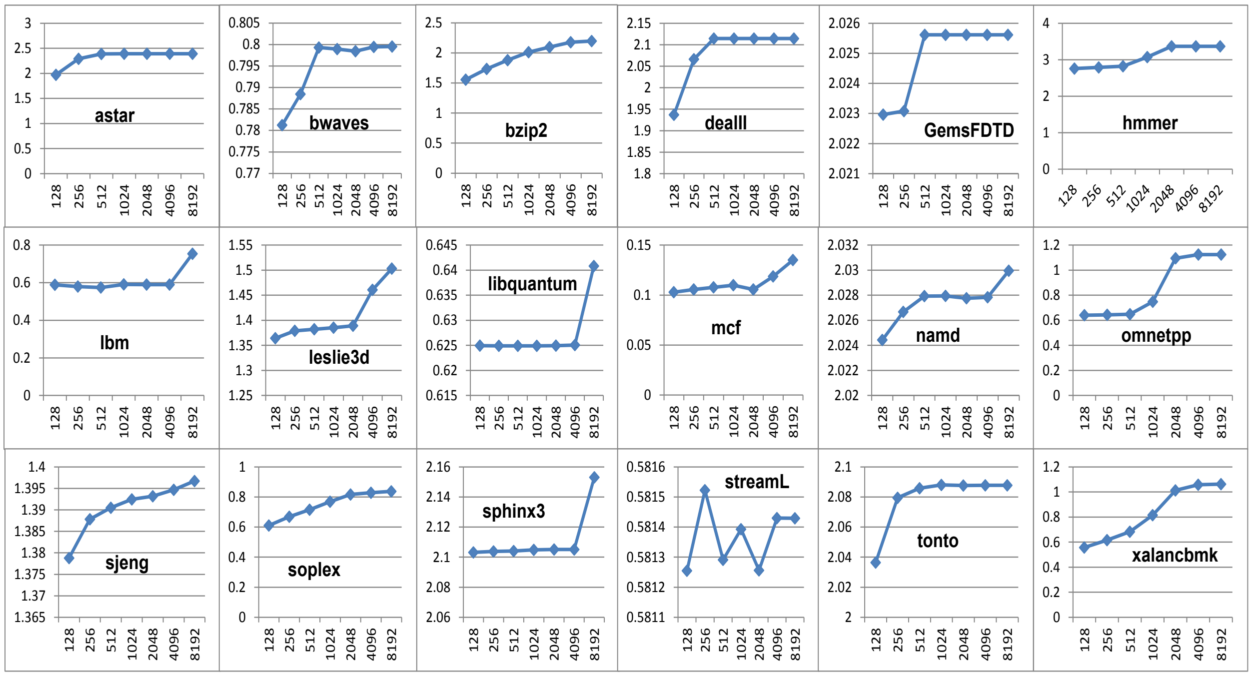


Fig. 9: IPC for different size of LLC.

$$M = \begin{array}{c} \\ App1 \\ App2 \\ App3 \\ App4 \\ App5 \end{array} \begin{array}{c} \begin{array}{ccccc} 1way & 2way & 4way & 8way & 16way \end{array} \\ \begin{pmatrix} 1.9 & 1.7 & 1.5 & 1 & 0.9 \\ 1.6 & 1.3 & 1.1 & 0.8 & 0.7 \\ 1.4 & 1.0 & 0.6 & 0.5 & 0.4 \\ 0.3 & 0.6 & 0.9 & 1.2 & 1.4 \\ 0.7 & 0.8 & 1.1 & 1.4 & 1.7 \end{pmatrix} \end{array} \quad (5)$$

In the first iteration of the bidding, the first 3 applications bid for the most profitable resource which is 128kB cache and they submit a bid equal to the difference of profit between the first and the second most profitable resource. Therefore, the first application, submits 0.2 bid to 128kb and the second application submits 0.3 and the third application submits 0.4. Since only one of the players can aqcuire the 128kB cache space, the first application will get it. The 4th and 5th application compete for 2MB cache space and they both get it with the sum bid of both which is 0.5. In the next round, the prices will be updated and since apllications 2 and 3 don't have any cache assignment compete for the 256kB cache space and each bid 0.2 which is the difference between 1.7 and 1.5 and 1.3 and 1.1 in the performance matrix accordingly. Since the second level cache can accomodate both applications the price will be updated and the minimum bidding price for some one to get this cache level is updated to the minimum bid of both which is 0.2. Therefore, if some application bid more than 0.2 it can acquire the resource and the application with smallest bid has to resubmit the bid to acquire the resource. Figure 10a, 10b, and 10c show the bidding steps and the prices and minimum price of bidding accordingly. As seen from the figures, the auction terminates in three iterations when there exists five applications.

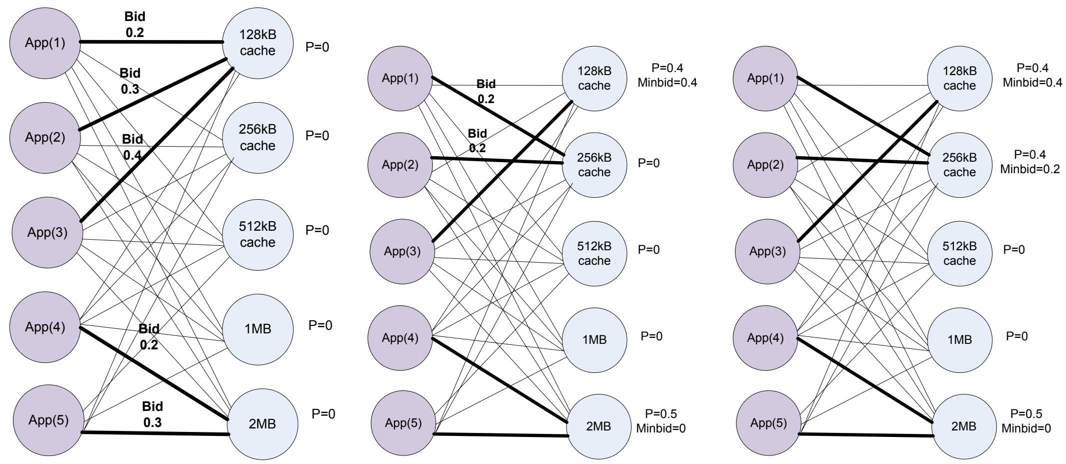
Next, we use different mixes of 4 to 16 applications from *Spec 2006* to evaluate the performance of our proposed approach. Figure 11 shows the normalized throughput of 10 different mix of applications using CAGE, equal private cache partitions and completely shared cache space. Figure 12 shows the scalability of our proposed algorithm. When the number of co-runners increases from 2 to 16, the performance improves from 12.4% to 33.6% without any need to track each applications' performance in a central hardware.

5 Related Work

With rapid improvement in computer technology, more and more cores are embedded in a single chip and applications competing for a shared resource is becoming common. On the one hand, managing scheduling of shared resources for large number of applications is challenging in a sense that the operating system doesn't know what is the performance metric for each application. But on the other hand, the operating system has a global view of the whole state of the system and can guide applications on choosing the shared resources.

There has been several works, for managing the shared cache in multi-core systems. Qureshi et al. [13] showed that assigning more cache space to applications with more cache utility does not always lead to better performance since there exists applications with very low cache reuse which may have very high cache utilization.

Several software and hardware approaches has been proposed to find the optimal partitioning of cache space for different applications [3]. However, most of these approaches use brute force search of all possible combinations to find the best cache partitioning in run time or introduce a lot of overhead. There has been some approaches which use binary search to reduce searching all possible combinations [5], [14], [43]. But none of these methods are scalable for the future many-core processor designs.



(a) first round. (b) second round. (c) third round.

Fig. 10: Cache allocation, a) first round, b) second round and c) third round of bidding.

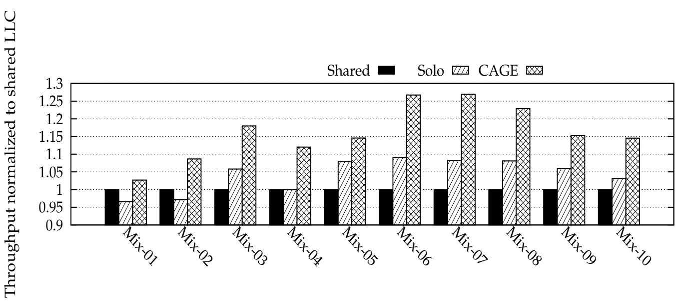


Fig. 11: Throughput of a shared, solo and CAGE cache allocation schemes.

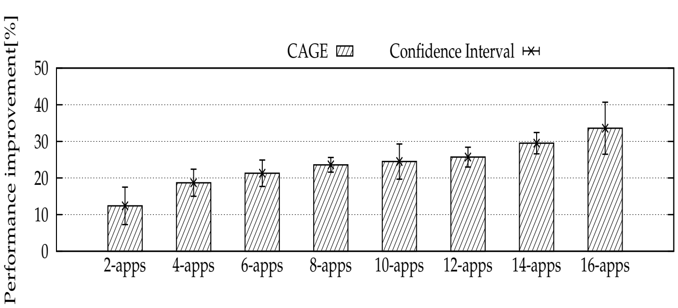


Fig. 12: Performance improvement of CAGE for different number of applications with respect to shared LLC for the case study of cache congestion game.

There exists prior game-theoretic approaches designing a centralized scheduling framework that aims at a fair optimization of applications' utility [28], [29], [30], [31], [32]. Zahedi et al. in REF [28], [31] use the Cobb-Douglas production function as a fair allocator for cache and memory bandwidth. They show that the Cobb-Douglas function provides game-theoretic properties such as sharing incentives, envy-freedom, and Pareto efficiency. But their approach is still centralized and spatially divides the shared resources to enforce a fair near-optimal policy sacrificing the performance. In their approach the centralized scheduler assumes all applications have the same priority for cache and memory bandwidth, while we do not have any assumption on this. Further, our auction-based resource allocation can be used for any number of resources and any priority for each application and the centralized scheduler does not need to have a global knowledge of these priorities.

Ghodi et al. in DRF [30] use another centralized fair policy to maximize the dominant resource utilization. But in practice it is not possible to clone any number of instances of each resources. Cooper [29] enhances REF to capture colocated applications fairly, but it only addresses the special case of having two sets of applications with matched resources. Fan et al. [32] exploits computational sprinting architecture to improve task throughput assuming a class of applications where boosting their performance by increasing the power.

While all prior works use a centralized scheduling that provides fairness and assume the same utility function for all, co-runners might have completely diverse needs and it is not efficient to use the same fairness/performance policy across them. In our auction-based resource scheduling provides scalability since individual applications compete for the shared resources based on their utility and the burden of decision making is removed from the central scheduler. We believe future CMPs should move toward a more decentralized approach which is more scalable and provides fair allocation of resources based on applications' needs.

Auction theory which is a subfield of economics has recently been used as a tool to solve large scale resource assignement in cloud computing [44], [45]. In an auction process, the buyers submit bids to get the commodities and sellers want to sell their commodities with the maximum price as possible.

Our auction-based algorithm is inspired by work of Bertsekas [33] that uses an auction based mechanism for network flow problems. Our algorithm is an extension of local assignment problem proposed by Bertsekas et al that has been shown to converge to the global assignment within a linear approximation.

6 Conclusion

The paper proposes a distributed resource allocation mechanism for large scale servers. The traditional resource management system are not scalable, especially when tracking the application's dynamic behavior. The main cause of this complexity is the centralized decision making which leads to higher time and space complexity. With increasing number of cores per chip, the scalability of assigning different resources to different applications becomes more challenging in future generation CMP systems. In addition, diversity in application's need make a single objective function inefficient to get an optimal and fair performance metric.

We introduce a framework to map the allocation problem to the known auction economy model where the application get virtual money and based on the utility metric they compete for the shared resource.

7 Appendix

In this section, we show that when the number of applications is large enough, CAGE is strategy-proof, such that no application can get more utilization by bidding more or less than the true value of the resource.

Proof of Theorem 1 Suppose all other players bidding strategy is to choose $\frac{n-m}{n-m+1}v_i$. Since the bidding values were derived uniformly in $[0,1]$ all bids have the same probability. Therefore, if we consider the first player's expected utility to find its best response, we have:

$$E[u_1] = \int_0^1 .... \int_0^1 (v_1 - b_1)\, \mathrm{d}u_2 \mathrm{d}u_3 ... \mathrm{d}u_{n-m}. \tag{6}$$

The following integral breaks into two part where the first player wins the auction or not.

$$\begin{aligned} E[u_1] = & \int_0^{\frac{n-m+1}{n-m}b_1} .... \int_0^{\frac{n-m+1}{n-m}b_1} (v_1 - b_1)\, \mathrm{d}u_2 ... \mathrm{d}u_{n-m} \\ & + \int_{\frac{n-m+1}{n-m}v_1}^1 .... \int_{\frac{n-m+1}{n-m}v_1}^1 (v_1 - b_1)\, \mathrm{d}u_2 \mathrm{d}u_3 ... \mathrm{d}u_{n-m} \end{aligned} \tag{7}$$

The second part of the integrals is the term where the first player doesn't win the auction. Therfore, the expected payoff of player 1 is equal with:

$$\begin{aligned} E[u_1] = & \int_0^{\frac{n-m+1}{n-m}b_1} .... \int_0^{\frac{n-m+1}{n-m}b_1} (v_1 - b_1) \mathrm{d}u_2 ... \mathrm{d}u_{n-m} \\ & = (\frac{n-m+1}{n-m} b_1)^{n-m} (v_1 - b_1). \end{aligned} \tag{8}$$

Differentiating with respect to b_1 the optimal bid for player one is derived as follows:

$$\frac{\partial}{\partial b_1}((\frac{n-m+1}{n-m} b_1)^{n-m} (v_1 - b_1)) = 0. \tag{9}$$

Which gives us the optimal bid for each player:

$$\Rightarrow b_1 = \frac{n-m}{n-m+1} v_1 \tag{10}$$

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