dJay : Enabling High-density Multi-tenancy for Cloud Gaming Servers with Dynamic Cost-Benefit GPU Load Balancing

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Abstract

In cloud gaming, servers perform remote rendering on behalf of thin clients. Such a server must deliver sufficient frame rate (at least 30fps) to each of its clients. At the same time, each client desires an immersive experience, and therefore the server should also provide the best graphics quality possible to each client. Statically provisioning time slices of the server GPU for each client suffers from severe underutilization because clients can come and go, and scenes that the clients need rendered can vary greatly in terms of GPU resource usage over time.

In this work, we present `dJay`, a utility-maximizing cloud gaming server that dynamically tunes client GPU rendering workloads in order to 1) ensure all clients get satisfactory frame rate, and 2) provide the best possible graphics quality across clients. To accomplish this, we develop three main components. First, we build an online profiler that collects key cost and benefit data, and distills the data into a reusable regression model. Second, we build an online utility optimizer that uses the regression model to tune GPU workloads for better graphics quality. The optimizer solves the Multiple Choice Knapsack problem. We demonstrate `dJay` on two high quality commercial games, Doom 3 and Fable 3. Our results show that when compared to a static configuration, we can respond much better to peaks and troughs, achieving up to four times the multi-tenant density on a single server while offering clients the best possible graphics quality.

Categories and Subject Descriptors C.2.4 [*Computer-Communication Networks*]: Distributed Systems—Distributed Applications; I.6.8 [*Simulation and Modeling*]: Types of Simulation—Gaming

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1. Introduction

Gaming is popular. Recently, cloud gaming — where datacenter servers host game application instances and clients merely transmit UI input and display output (e.g. frame buffers) from servers — has emerged as an interesting alternative to traditional client-side execution. Sony's PlayStation Now, Nvidia's GRID and Amazon's AppStream are among the cloud gaming services available to consumers today [1, 3, 4].

Cloud gaming offers several advantages. Client-side system configuration and platform compatibility issues are eliminated, alleviating a long-standing headache of traditional non-console gaming and mobile device gaming. In addition, upgrading datacenter servers with better hardware is far easier than redeploying hardware to clients. Furthermore, players can select from a vast library of games and instantly play any of them.

However, cloud gaming faces several technical challenges that are not unfamiliar to other cloud service providers: latency, bandwidth and multi-tenancy [6]. Previous work has looked at reducing cloud gaming's latency and bandwidth costs [8, 20]. In this work, we tackle multi-tenancy: how can a server host as many players as possible? Multi-tenancy's importance is underscored by the lessons of one early cloud gaming pioneer, which failed in part because it could only support one client per server, thereby making a large and ultimately unsustainable investment in server farms [13].

At first, it might appear that the same isolation and virtualization support that has served traditional hosted services well would suffice for multi-tenant gaming. However, cloud gaming multi-tenancy is challenging and distinct from traditional datacenter multi-tenancy because games exhibit three unique properties.

- **GPU-Centric Workload:** Graphics rendering is heavily reliant upon the GPU. System resources such as disk, system memory and CPU are often underloaded.
- **Continuous Deadlines:** Acceptable gaming interactivity requires continuous frame processing of at least 30 Frames Per Second (FPS) for the whole session. Players become dissatisfied when frame rates fall below 30 FPS [7].

- **Adjustable Visual Quality:** Games typically expose many optional *graphical effects* (e.g., anti-aliasing, texture details, shadows) that produce higher quality graphics. Provided at least 30 FPS, players prefer the highest possible visual quality.

Naïvely running multiple tenants concurrently on a server can pose grave shortcomings. The load generated by one instance can squeeze out another instance, resulting in missed deadlines, low or erratic frame rates and an unplayable experience. Even the load generated by a single instance exhibits significant temporal variability due to *scene complexity*: simple scenes with a few basic objects and no effects such as Figure 1a render much faster than complex scenes with many detailed objects and complex lighting and advanced effects such as Figure 1b. Players can encounter both simple and complex scenes within a brief window of a single session. Therefore, if a server chooses to statically provision for the worst case of all players visiting complex scenes all the time, wasted resources and over-provisioning will be significant.

To address these shortcomings, we have built `dJay`,[1] a game hosting server (akin to an application server) that maximizes aggregate visual quality while meeting all deadlines in the face of both variable scene complexity and client churn. Central to `dJay` is the notion of *utility*, which we define to consist of two components: *cost* in terms of GPU time, and *benefit* in terms of visual quality. Examples of better and worse visual quality are higher and lower resolution, respectively. Utility is the basis for `dJay`'s three main functions which enable it to maximize aggregate visual quality.

Online Utility Pofiling: `dJay` first constructs a utility profile per application. During this one-time operation, `dJay` collects utility measurements from live sessions. A core part of the profiling is that `dJay` distills data collected from sessions into *per graphical object utility*, where graphical objects are things that appear in game (*e.g.,* race cars, buildings, soldiers). This step is important because object utilities are reusable across sessions, whereas session utilities are not. The distillation occurs through regression model construction. §4 describes utility profiling in detail.

Future Utility Estimation: After the regression model is constructed, `dJay` actively monitors each live session to determine whether a session's utility will change significantly in the near term (which can happen often, for example, due to scene changes). To produce an accurate estimate, `dJay` queries the game for a list of game objects, and applies the regression model to the objects, and generates an estimate of expected future utility. §5 describes utility estimation in detail.

Expected Utility Maximization: Lastly, `dJay` dynamically adjusts visual quality settings to deliver the best possible aggregate quality. It does so by periodically solving a visual quality optimization problem subject to GPU demands

[1] `dJay` : a music artist that plays and mixes multiple records simultaneously.

(a) Simple Scene (b) Complex Scene

Figure 1: Scene complexity examples from Fable 3.

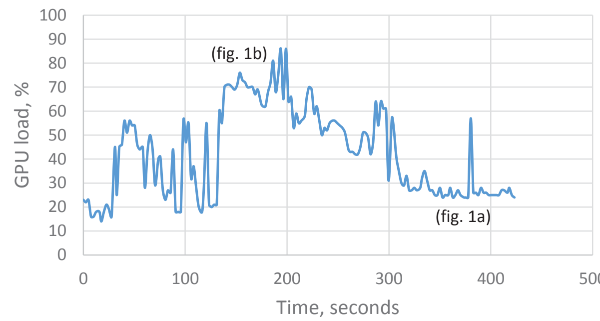


Figure 2: GPU load varies considerably during the course of a Fable 3 session.

and resource availability. We map our problem to the well known Multiple Choice Knapsack Problem [17], for which we adapt a fast heuristic. Furthermore, `dJay` ensures that quality changes are not disruptive to player experience by employing a graceful quality change process. §6 describes utility optimization in detail.

We have ported two high-quality production games, Fable 3[2] and Doom 3[3], to run on `dJay` (§7). The evaluation in §8 shows that `dJay` is not only able to effectively profile and predict utility, it is also able to dynamically optimize visual quality to enable up to 4× more multi-tenancy than the comparable baseline. Lastly, `dJay`'s system overhead is low (less than 3ms per frame), which is extremely important for an interactive cloud gaming system.

2. Background

For gaming, GPU processing is the bottleneck resource. One avenue to multi-tenancy is to create a static partitions of the GPU for each application instance. Commercial GPU virtualization solutions from Citrix and VMWare already provide this capability. However, this leads to very poor server density for two reasons. First, users come and go, making static partitions unaccommodating. Second, a game's scene complexity and corresponding GPU load can change dramatically over time. For example, a user in a virtual environment may view a simple room at one moment and then navigate to view a complex garden environment in the next moment. Unfortunately, a static partition must allocate conservatively for peak load since poor frame rate during some scenes is un-

[2] `http://www.lionhead.com/games/fable-iii/`

[3] `http://bethsoft.com/en-us/games/doom_3_bfg`

satisfactory. This means during any non-peak load — which occur frequently — GPU cores sit idle. Figure 2 shows that for a typical application, much GPU capacity remains idle for much of the time. The timespans of high utilization and low utilization correspond to scenes like Figure 1b and Figure 1a, respectively. This waste leads to inefficient operations on the part of the service providers.

We observe that almost all games provide the capability to tune *rendering settings*. Common examples of rendering settings include screen resolution, antialiasing, lighting model complexity, enabling or disabling shadows, and texture detail. Developers offer these knobs because end user machines vary greatly in capability. With traditional thick clients (no cloud gaming), a user with a powerful machine can enable many advanced rendering settings whereas a user with a modest machine can tone down settings in order to maintain a responsive FPS. A speed of 30 FPS is widely regarded as the threshold for a playable experience. Therefore, we treat its inverse, 33ms per frame, as the maximum permissible *frame time*. Since frame rates above 30 FPS have marginal benefits [7], in this work we consider any frame time 33ms or below equally acceptable.

We leverage the rendering settings that titles already expose as the means to trade off better visual quality for lower resource utilization. Games commonly contain a fixed number of preset rendering settings such as High, Medium and Low, which in turn map to various settings for individual rendering parameters (e.g., High gives 16× antialiasing, maximum texture detail, etc.). It is worth noting that changes in rendering settings are strictly visual enhancements and have no bearing on game semantics. Therefore, we are free to alter rendering settings at any time without side effects on game logic.

We also introduce the *Structural Similarity (SSIM)* score, a standard criteria of the video compression community used to quantify the perceived loss in video quality between a pristine image f^* and a distorted version of the image, f [26]. For example, the images f^* and f might represent the same scene rendered with a High setting and a Medium (or Low) setting, respectively. The function $SSIM_{f^*}(f)$ takes a real value in $[0,1]$ where a lower values indicates lower fidelity to the pristine image. By definition, $SSIM_{f^*}(f^*) = 1$ and $SSIM_{f^*}(f) = 0$ when f is random noise. While SSIM is not perfect at reflecting human subjective assessment of quality, it is more accurate than alternative measures such as SNR and PSNR, and maps reasonably to the standard subjective user-study based measure for video quality, Mean Opinion Score [26].

3. Approach

Given a fixed budget of 33ms per frame, the questions we aim to address are:

- **Cost:** What rendering settings are feasible?
- **Benefit:** Among the feasible, which setting is best?

These turn out to be challenging questions for two reasons. First, the feasible combinations depend greatly on the GPU cost of the workload at hand. As previously noted, scene complexity can change anytime. A rendering setting that is feasible for the current scene in the game may be too expensive for other scenes in the game. Second, among those feasible rendering settings, the “best” can differ depending upon the scene. For example, consider the two renderings of the same arch scene shown in Figure 3. There are very noticeable differences in the landscape between the high quality and low quality renderings. In contrast, the high and low quality renderings of a coastal scene shown in Figure 4 look very similar. Therefore, we cannot assume that the benefits of more sophisticated rendering apply uniformly to all scenes.

Figure 5 illustrates the architecture of `dJay` by which we resolve these questions about cost and benefit. We next describe its main pieces.

3.1 Measuring Cost

In order to understand which combinations of rendering settings are feasible, we build profiles of each app’s frame time under different rendering settings. However, frame time alone lacks context; given a rendering setting, we lack any notion of what may be causing higher or lower frame time. Without additional context, we are limited to attributing (high) frame times to coarse app-level granularity. This worst case estimate attains no better resource utilization than conservative static partitioning.

Ideally, we ought to map frame time to relevant in-game context. We conjecture that *graphical objects* can serve as useful context because they can have a large impact on frame time. As a concrete example, graphical objects in Fable 3 include castles, houses, enemies and non-player characters, to name just a few. Graphical objects are created at the discretion of the app developers and a typical game contains hundreds to thousands. Since a castle object is graphically much more complex than a house object, we aim to attribute a higher GPU cost to castles than to houses. Suppose for every frame, the game provides us the *active object list* (AOL), the list of graphical object types used to render the frame. By mapping cost to graphical objects, we can later estimate a cost for a *novel* scene based on the graphical object types it contains. `dProf` shown in Figure 5 is the component that measures costs and performs the mapping of costs to graphical objects. We use statistical *regression models* to determine the cost-to-object mapping (§4).

3.2 Measuring Benefit

In order to objectively assess “best,” we use SSIM and compare rendering settings as follows for a given scene. Suppose we generate the pristine image f^* with rendering settings R^* where R^* is the setting with every optional rendering setting dialed to maximum quality. Let R_1 and R_2 be two rendering settings and let f_1 and f_2 be the images generated by them,

(a) High Quality (b) Low Quality

Figure 3: Major differences between High and Low Quality.

(a) High Quality (b) Low Quality

Figure 4: Minor differences between High and Low Quality.

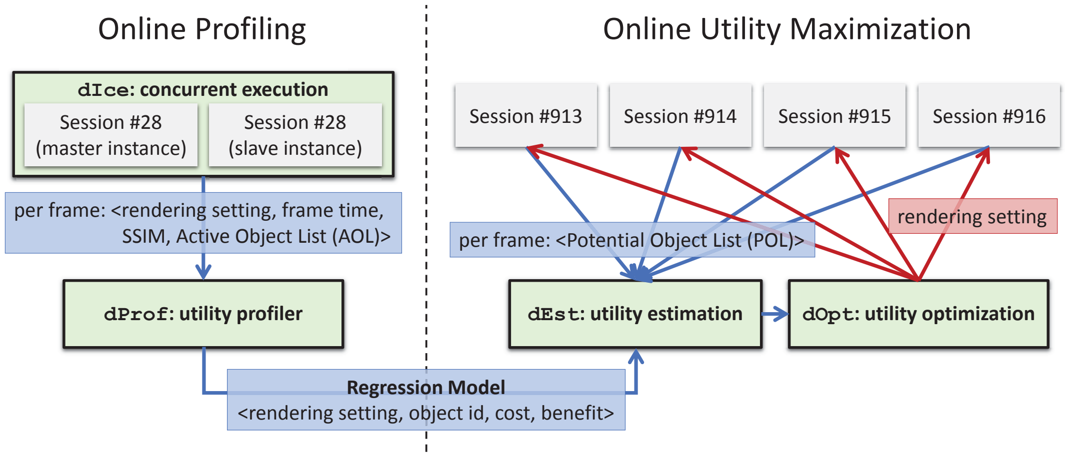


Figure 5: The dJay architecture shows the relationship of various components, all of which run online. Blue arrows represent measurement whereas red arrows represent control.

respectively. We say $R_1 > R_2$ if $SSIM_{f^*}(f_1) > SSIM_{f^*}(f_2)$. However, comparing the SSIM of two existing frames is insufficient to tell us about the SSIM of a novel frame that we encounter in the future.

As with frame time, we wish to generalize SSIM beyond a single frame. Therefore, we employ an approach for SSIM that is similar to the approach that we employed for frame time. dProf also uses statistical regression to map the SSIM of a frame to the SSIM contribution of graphical objects in the frame, thereby deriving a per-object "benefit" measurement (§4). These benefit values are opaque in that they cannot be interpreted as SSIM per se. We show how they are used next.

3.3 Estimating Future Utility

With regression models constructed, our next task is to apply the models at runtime to estimate the *utility* — the benefit-to-cost ratio — of upcoming scenes for various rendering settings. This is performed by dEst. Two aspects worth elaboration are 1) why we work on upcoming scenes, and 2) how we estimate the utility of various rendering settings.

First, we focus on upcoming scenes (as opposed to past scenes or the current scene) because upcoming scenes are the ones for which we still have the opportunity to adjust rendering settings. The main challenge is to identify upcoming scenes in a reasonable way. We introduce the notion of a *potential object list* (POL). The POL consists of those game object types that are likely to be encountered by the player within a short time horizon. For example, a castle just beyond the player's field of view is a good candidate for the POL. dEst receives POL updates from the game dynamically.

Second, we estimate utility with respect to both current and alternative rendering settings. Estimation for one rendering setting consists of using the regression model to perform a statical inference. dEst makes the estimate for each rendering setting to arrive at a collection of utilities, one for each rendering setting.

3.4 Optimization

dOpt takes the future utilities computed by dEst for all sessions, computes a utility-maximizing assignment of rendering settings to sessions, and then propagates the new rendering settings to the corresponding sessions. The utility maximization problem nicely maps to the Multiple Choice Knapsack Problem, for which polynomial time approximations are available [17, 22]. However, we choose a simpler greedy heuristic because dOpt must complete its online decision making very quickly. In addition, we incorporate a limited form of hysteresis into our heuristic such that visual quality changes are gracefully made when possible, and quickly enacted when necessary.

3.5 Requirements

For dJay to work as described above, we require that:

1. An instance can report the AOL and POL for every frame.
2. An instance can change rendering settings dynamically.

Fortunately for Requirement 1, the AOL and POL are already maintained as part of standard rendering data structures like Octrees and k-d trees [10]. How an app maintains this data structure internally (tree, nested, graph, etc.) is an internal design decision. We simply require these be exposed to `dJay` as a generic flat namespace list. It is even permissible for the app to pass lists with extra or missing objects. This does not affect correctness; it will only impact how well `dJay` can optimize the density of the server. Therefore, it is straightforward for a developer to expose the AOL and POL to `dJay`; just pass the already-in-use rendering data structures as lists. For Requirement 2, games typically permit adjustment of rendering settings in-game, so it is straightforward.

4. Online Utility Profiling

We next describe the detailed operation of `dProf`.

4.1 Building Game Object Profiles

From a session s with a fixed rendering setting r, `dEst` screen captures a set of uncompressed frames, $f_1^{sr}, f_2^{sr}, \ldots, f_N^{sr}$. Due to storage constraints, it may be a subset of the frames that the user actually sees during the session. From each frame f_i^{sr}, we measure its cost in terms of GPU frame time, c_i^{sr}, and its benefit in terms of SSIM b_i^{sr}. We also require that the game report the frame's AOL, which is a list of graphical objects, $G_i^{sr} = \{g_{ij}^{sr}\}$ where j is the unique ID of each game object type (e.g., `castle_type_42`) and g_{ij}^{sr} represents the number of game objects of type j in frame i of session s with rendering setting r.

In order to build a per-game object profile, we construct a system of equations as follows.

$$\sum_j w_j^b g_{ij}^{sr} = b_i^{sr} \qquad \forall i,s,r$$
$$\sum_j w_j^c g_{ij}^{sr} = c_i^{sr} \qquad \forall i,s,r$$

where w_j^c and w_j^b are the weights for cost and benefit, respectively. We use a least squares method to determine the unknown weights. Weights essentially encode per-game object profile information. Note that a game object whose impact on cost and/or benefit is high will naturally be assigned a higher weight. Note also that measurements from additional sessions simply result in more equations, leading to more refined weightings. Alternative models such as nonlinear and neural networks are also feasible. We tried some of these and found the simple linear model to work surprisingly well in practice. Lastly, weights need not be pinpoint precise as long as they are informative enough to guide cost-benefit decisions.

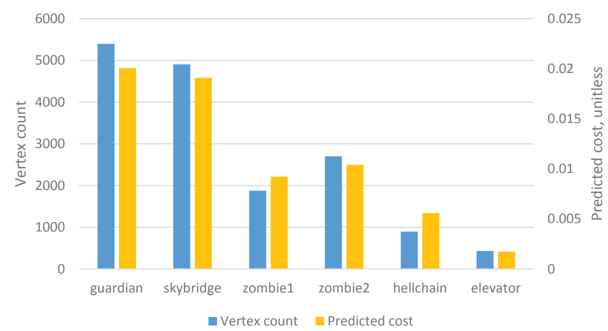


Figure 6: Vertex count correlates well with graphical object cost. Therefore, a coarse filter eliminates unimportant objects by their vertex count. Shown here is a small random sampling of over 130 Doom 3 objects. The names "guardian," "skybridge," etc. are the original object names given by the Doom 3 developers.

4.2 Deterministic Instance Concurrent Execution

While measuring GPU cost is straightforward, measuring SSIM benefit is more nuanced. Recall that in §3.2 we introduced the function $SSIM_{f_i^*}(f_i)$ where some frame f_i is evaluated against a pristine f_i^*. A key question is how to obtain f_i^*. To accomplish this, we employ *deterministic instance concurrent execution* (`dIce`) shown in Figure 5. The essential idea is to run two instances — a master and a slave — of the same game concurrently. The instances differ only in their rendering settings such that the master produces $f_1^*, f_2^*, \ldots, f_N^*$ and the slave produces $f_1, f_2, \ldots, f_N$. The instances are identical in all other respects: the instances start in the same initial state, receive the same user input during the session and process the input deterministically to arrive at new intermediate states.

A key requirement of the app is that the app should act deterministically given user input. Previous work has shown that modern games can be modified in a generic way (e.g., converting `getTime()` calls to return deterministic values based on a fixed hash seed) to achieve the required input determinism [8]. `dIce` pipes user input to both concurrent instances. The two instances respond deterministically to the input, differing only in the visual quality of their rendered output.

Since profiling requires running an extra slave for every master, we recommend running profiling during quiescent periods such as 1) during new game onboarding where user access to the new game is rate limited, and 2) during diurnal troughs in utilization (e.g., 5am in the morning) when the service experiences light utilization.

4.3 Object Filtering

While the per-object profile construction described above works, it has the potential to create performance issues, especially if the app passes large lists of graphical objects to `dProf` at every frame. To mitigate this issue, we prune the

AOL with two filters as follows. First, we coarsely filter the objects by their *vertex count*, which is the number of vertices in the object's 3D representation. Objects that are more expensive to render tend to have more vertices. Figure 6 illustrates this relationship by showing the tight correlation between an object's vertex count and the object's predicted cost, w_j^c. We prune objects whose vertex count is below a threshold ε_v. Second, we finely filter the objects by their cost and benefit weights. The reason that a second level of filtering is necessary is because the object list may still be too large with just coarse-grained vertex-based filtering. In order to filter by weights, we first construct an initial regression model with only vertex-based filtering to arrive at some initial weights. We then filter object type j if either cost or benefit weight is less than ε_w. Finally, we construct a new regression model with the remaining objects, arriving at final weights w_j^b and w_j^c. We have empirically found setting ε_v to 100 vertices and ε_w to 0.0001 to work well in practice.

5. Future Utility Estimation

Next, `dEst` uses the weights of the linear regression from `dProf` to forecast upcoming cost and benefit. However, we do not have exact information about future objects since these are dependent upon the user's upcoming actions which are obviously not known. Instead, we use the POL $\hat{G}_i^{sr} = \{\hat{g}_{ij}^{sr}\}$, that are likely to be visible within a short time horizon. Its notation mirrors that of G: i is the frame number and j is the unique id of the game object. We rely on the game to provide updates of $\hat{G}$ to `dEst`, just like we relied on the game to provide G to `dProf`. $\hat{G}$ only needs to be a guess, not exact; better guesses lead to more accurate utility estimates. Providing $\hat{G}$ is also straightforward for game developers in practice, as we discussed in §3.5.

In order to estimate upcoming cost $\hat{c}_i^{sr}$ and benefit $\hat{b}_i^{sr}$ for $\hat{G}_i^{sr}$, we apply the regression model as follows.

$$\hat{b}_i^{sr} = \sum_j w_j^b \hat{g}_{ij}^{sr}$$
$$\hat{c}_i^{sr} = \sum_j w_j^c \hat{g}_{ij}^{sr}$$

Cost and benefit are calculated for every frame, which is feasible since the calculation is very fast.

6. Expected Utility Maximization

Finally, `dOpt` uses the estimated future utilities to decide on the visual quality for each session. If costs are expected to rise, `dOpt` should downgrade the sessions that suffer little quality drop but return significant resource savings. Conversely, if costs are expected to fall, `dOpt` should upgrade the session that gets the most visual quality improvement from the extra resources newly available. In addition, `dOpt` should gracefully change visual quality when possible so that visual quality changes are not too abrupt for users.

6.1 Optimization Problem and Initial Assignment

The task is to assign rendering settings to each active session. We choose to make the assignment such that the aggregate utility is maximized. Other optimization objectives (such as maximizing the minimum utility, maximizing fairness, etc.) are also interesting and we leave them for future work.

From `dEst`, we have a set of utilities $U = \{(\hat{b}^{sr}, \hat{c}^{sr})\}$, each of which corresponds to an active session s and rendering setting r pairing (we drop the per-frame subscript i since we only discuss a single time step). The objective function is to maximize the aggregate expected utility:

$$\text{Maximize} \quad \sum_s \sum_r x^{sr} \hat{b}^{sr} \tag{1}$$

where x^{sr} is an indicator variable that is 1 if rendering setting r is chosen for session s and is 0 otherwise. The constraints are that the total expected cost should be less than the minimum acceptable frame time, 33ms, and that each session should be assigned a rendering setting:

$$\sum_s \sum_r x^{sr} \hat{c}^{sr} < 33\text{ms} \tag{2}$$
$$\sum_r x^{sr} = 1 \qquad \forall s \tag{3}$$

This formulation is a classic variation of the knapsack problem, known as the multiple choice knapsack problem (MCKP) [22]. It is NP-hard. We employ a greedy heuristic for MCKP which is inspired by the heuristic presented in [17]. The idea behind the heuristic is to transform MCKP into a version of the regular knapsack problem, and apply the standard greedy solution of the regular (non-multiple choice) knapsack problem. The key intuition is that we enforce every session to have at least some rendering setting assigned by first assigning all sessions to the lowest rendering setting. Some residual capacity less than 33ms may be left over for upgrading some sessions to higher rendering settings. We then rank all the remaining $(\hat{b}^{sr}, \hat{c}^{sr})$ pairs by their utilities in descending order. However, rather than ranking by absolute utility, we rank by *marginal* utility, which we define as the increase in utility of one rendering setting over the least costly rendering setting of the same session. That is, the marginal utility is:

$$u^{sr} = \frac{\hat{b}^{sr} - \hat{b}^{sq^*}}{\hat{c}^{sr} - \hat{c}^{sq^*}}$$
$$q^* = \operatorname*{argmin}_q \hat{c}^{sq}$$

Finally, we iteratively pick the top ranked candidate until we run out of residual capacity. Whenever we pick a candidate that belongs to session s, we simultaneously excise all other pairs belonging to s from the ranked list. Our heuristic differs from that of [17] in that they are willing to tolerate exceeding the capacity for sake of a solution that is closer to optimal whereas we are not.

$s=1$	Rendering Setting LO $r=1$	ME $r=2$	HI $r=3$
$\hat{b}^{sr}$	0.7	0.8	0.95
$\hat{c}^{sr}$	2	5	29

(a) Session 1

$s=2$	Rendering Setting LO $r=1$	ME $r=2$	HI $r=3$
$\hat{b}^{sr}$	0.9	0.94	0.96
$\hat{c}^{sr}$	10	14	15

(b) Session 2

Table 1: An example of two sessions and their corresponding cost and benefits for three rendering settings: LO(W), ME(DIUM) and HI(GH). The `dOpt` heuristic identifies ME and HI for Session 1 and 2, respectively, as explained in the text.

As an illustration, consider the following example shown in Table 1 with two sessions and three rendering settings. The residual cost is $33-2-10=21$. The ranked utilities are: $u^{1,2}=\frac{0.1}{3}$, $u^{2,3}=\frac{0.06}{5}$, $u^{2,2}=\frac{0.04}{4}$ and $u^{1,3}=\frac{0.25}{27}$. We first pick $u^{1,2}$ which reduces the remaining frame time to $21-3=18$. We also remove $u^{1,3}$ from the list. We then pick $u^{2,3}$ which reduces the remaining frame time to $18-15=3$. We also remove $u^{2,2}$ from the list. At this point, no more candidates remain in the list so the heuristic terminates.

The benefit of the greedy heuristic is that it is both simple and fast: it runs in time $O(n\log n)$ due to the need to sort, where n is the number of sessions times the number of rendering settings. Speed is of particular importance because the heuristic is responsible for online decision making.

6.2 Graceful Change During Normal Operation

We run the heuristic once per epoch, where an epoch is five frames. The cost and benefit used are the average cost and benefit over the last epoch. However, dynamically changing rendering settings arbitrarily can be too abrupt, even once per epoch. A rendering setting that changes from one extreme of high quality to the other extreme of low quality could be easily noticed by the user. We protect against abrupt changes by only permitting rendering settings that are one level higher or one level lower than the current rendering setting, in addition to staying at the same rendering setting. We implement this change by modifying the above MCKP heuristic as follows. At epoch t, instead of initializing the heuristic by setting all sessions to the lowest rendering setting, we set all sessions to their rendering settings determined in epoch $t-1$. If the residual frame time is greater than zero, we have the chance to upgrade some rendering settings as before. However, instead of considering all possible rendering settings in the ranking, we only consider those rendering settings that are one level higher than the current setting. We pick top ranked utilities from the list as before. Continuing from the example in Table 1, suppose in Epoch 1 we have made the selections of rendering setting 2 for session 1 and rendering setting 3 for session 2 as discussed above. Then in Epoch 2, we only consider rendering setting 3 for session 1 (as long as costs are equal or less than before). If instead the residual capacity is less than zero (indicating costs are greater than before), we are in the situation of needing to downgrade one or more session's rendering settings. We then construct a ranked list of marginal utilities in ascending order, but this time only for those rendering settings that are one level less than the current settings. We iteratively pick the top rank from this list until the cost is lowered enough to satisfy the frame time budget. Taking again the example in Table 1, suppose Epoch 1 is assigned as discussed previously, but this time in Epoch 2, all the costs double such that the residual frame time is now $33-5\times2-15\times2=-7$. The ranked list is then $u^{1,1}=\frac{-0.1}{-6}$ and $u^{2,2}=\frac{-0.02}{-2}$. In the first iteration, session 1 is downgraded to rendering setting 1, leaving $-7--6=-1$ residual frame time. in the next iteration, session 2 is downgraded to rendering setting 2, leaving $-1--2=1$ residual frame time.

It is possible that by limiting rendering setting increases to only one level higher, residual frame time may be wasted which otherwise might be spent toward an even higher rendering setting. Similarly, it is also possible that by limiting setting decreases to only one level lower, the total frame time may still exceed 33ms (i.e., negative residual frame time) whereas considering all possible rendering setting decreases may reveal setting(s) that achieve the 33ms target. In practice, we found that dampening changes is useful because 1) it minimizes abrupt changes that can distract users, and 2) if a better setting exists that is more than one step away, we can still converge to it eventually in future epochs.

It may be the case that we are unable to converge to 33ms even after several epochs. For this case, we use a two part fallback solution, called *Warning* and *Critical*. `dOpt` triggers the Warning condition when the total frame time is between 33ms and 40ms for more than 200 epochs, and triggers the Critical condition when the total frame time is more than 40ms for more than one epoch. If either Warning or Critical condition is triggered, all rendering settings are reassigned as described in §6.1. Critical is usually indicative of a session permanently transitioning from a scene with low complexity to a scene with high complexity, in which case we ought to downgrade right away to maintain a playable experience for all clients. Warning is afforded a longer interval since there can be many ephemeral instances where the utilization spikes briefly.

6.3 Managing Session Churn

User churn entails both starting and ending sessions. When a session ends, resources are freed up. We handle this case just as described for normal operations in §6.2; over one or more epochs, the remaining sessions will start to use up the newly freed resources. When a session starts, we take a two step approach. First, we try to add the new session at the highest possible rendering setting that fits in the residual frame time. In a fully loaded system, this often means that the new session can only be added at the lowest rendering system, if at all. If this fails (due lack of frame time budget), we then take a more drastic approach of reinitializing all rendering settings for all sessions as described in §6.1. There can be cases where even setting every session to the lowest rendering setting does not satisfy the 33ms budget. This indicates an admission control failure which we discuss in §10.

7. Implementation

To prototype `dJay` we modified open source Doom 3 (originally 366,000 lines of code) and Fable 3 (originally 959,000 lines of code) to interface with `dProf`, `dIce`, `dEst` and `dOpt` components. Modifications to the games was done via source code; `dProf`, `dEst` and `dOpt` were implemented as standalone console processes. The number of modified lines of code was 500 and 300 for Fable 3 and Doom 3, respectively. All instances run in the same host OS, Windows 8, because the two apps are written for the Windows platform but the Windows Hypervisor does not support high performance GPU virtualization. Other hypervisors such as VMWare and Citrix do not have this limitation. As a result, we rely on the host OS's and GPU device driver's core scheduling and memory management mechanisms, neither of which makes provisions for real-time guarantees, let alone while multiplexing the GPU. Therefore, our implementation provides a conservative reference point in terms of performance gains possible. Another limitation is that `dJay` only supports running one game type (either Fable 3 or Doom 3) at a time; future work includes load balancing across disparate apps at once on the same server.

We extended Doom 3 and Fable 3 to invoke the `dJay` API where appropriate. The API requires games to receive rendering setting change commands. The API also requires games to provide the following data for each in-game frame: current frame number, frame time, frame buffer, the AOL and the POL. The data is pulled by the API rather then pushed by the game to ensure minimum impact on the game performance. The data being pulled depends on the mode of operation: profiling or optimization.

7.1 Profiling mode

In profiling mode, the user plays normally on the best rendering settings while `dJay` records every frame's frame number, AOL, frame time and frame buffer into a file. Note that the largest item in this set, the frame buffer, is already being transferred to the encoder for streaming to the thin client and `dJay` merely needs to fork a copy. We modified each game to save the AOL as an array of object identifiers to a region of memory shared between the game instance and `dJay`. For both Doom 3 and Fable 3, we use the game's preexisting internal visible objects data structure as the basis for the AOL. Coarse-grained object filtering by vertex is implemented as part of the conversion from internal data structure to AOL.

In order to support deterministic concurrent execution, we first save the client's input stream to a buffer. When available, we take advantage of the fact that games sometimes support "replay mode" (aka "spectator mode") to replay the input stream in a separate instance of the same game at a different rendering setting. During replay mode, we also collect every frame's frame number, AOL, frame time and frame buffer as before. Doom 3 has replay mode built-in. Fable 3 does not have replay mode built-in so we implemented (deterministic) replay ourselves by adding the following command line options: `-capture` causes the game to dump keyboard, mouse and joystick commands along with the world-relative timestamps into a log file, `-replay` disables all regular game input and pushes fake commands into the game input queue in the moments of world-relative time which are specified in the log file. We patched Doom 3 and Fable 3 as described in [8] and [20] in order to enable deterministic replay. The collected datasets are then loaded into `dProf` to create the game's utility profile. `dProf` constructs and solves two systems of equations via least squares linear regression.

7.2 Optimization mode

In optimization mode, we modified the game to save the POL to the same shared memory as was used by AOL. In order to construct the POL for Fable 3, we use an internal method `checkVisibility(FoV)` that determines whether a graphical object is within a given field-of-view. We use `checkVisibility(360°)` on Fable's internal list of graphical objects to generate the POL. Doom 3's POL is similarly constructed. `dEst` reads the data from the shared memory, and runs the regression model. `dOpt` takes the estimated utilities, runs the optimization and updates the game with the corresponding rendering setting.

8. Evaluation

A summary of our findings are as follows.

- Regression modeling yields accurate utility estimates which can be used to estimate total frame time and SSIM score of the upcoming frames with a 15% L1 error.
- The median overhead of online profiling is 0.33ms. The median overhead of online estimation and optimization is 1.8ms.
- Dynamic utility maximization provides equal or better quality than static configurations. Gains are especially apparent when scene complexity changes and players churn. In the best case, `dJay` can scale to 4× more sessions than static.

8.1 Experimental Setup

We tested `dJay` prototype running on a single server that consists of an HP z820 server with quad core Intel i7, 16GB memory, and an Nvidia GTX 580 GPU w/ 3GB memory. The GTX 580 is similar to one discrete GPU chip of a server-class multi-chip rendering card such as the Nvidia GRID M40.

`dJay` was configured to support three rendering setting presets for each game: Low (LO), Medium (ME) and High

Rendering Setting	HI value	ME value	LO value
Video Quality	Ultra	High	Medium
High quality special effects	Yes	No	No
Antialiasing	16x	2x	Off

(a) Doom 3

Rendering Setting	HI value	ME value	LO value
Model detail	Very High	Normal	Very Low
Landscape detail	Very High	Normal	Very Low
Effects detail	High	Normal	Very Low
Tree detail	Very High	Normal	Very Low
Texture Quality	Very High	Normal	Very Low
Shadow Quality	Very High	Normal	Reasonable
Water Quality	Very High	Normal	Very Low
Draw distance	Very High	Normal	Very Low

(b) Fable 3

Table 2: Rendering Setting Presets. Values such as “Ultra,” “Very High,” “Reasonable” and so forth are constants defined by Doom 3 and Fable 3.

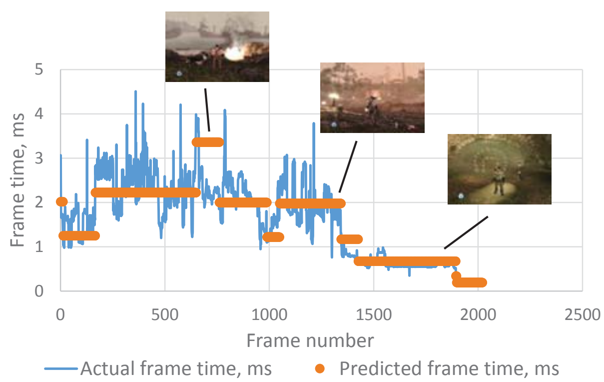


Figure 7: Predicted Frame Time vs. Actual Frame Time for Fable 3

(HI). Video settings used for Doom 3 are shown in Table 2a. Screen resolution was 1280×1024 for all presets, windowed mode. Video settings used for Fable 3 are shown in Table 2b. Screen resolution was 1920×1080 for all presets, in windowed mode. While our prototype can let users play interactively, we ran all of our experiments via automated scripts. We recorded approximately 30 hours of player traces per game covering many different in-game scenes to ensure data diversity. We reused the replay mode function built for `dIce` to inject prerecorded user traces to simulate live players. `dJay` was configured to keep frame rate above 30 FPS; service provider may choose a higher cap if so desired.

8.2 Utility Estimation Accuracy

To evaluate the regression model's estimation accuracy, we compared predicted frame time and SSIM with ground truth frame time and SSIM. We show the results for Fable 3 only as the results for Doom 3 are similar.

Figure 8: Predicted SSIM vs. Actual SSIM for Fable 3

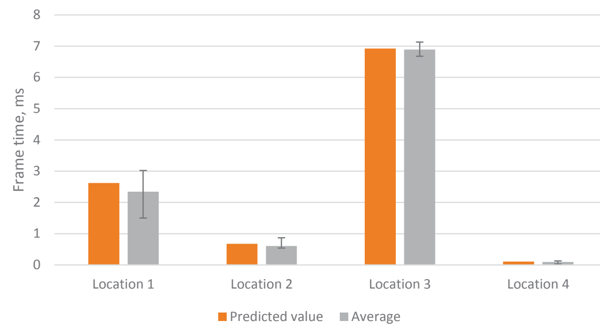
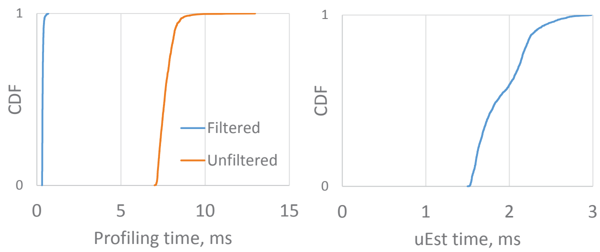


Figure 9: A Summary of Regression Model Accuracy. “Error bars” represent 95th and the 5th percentile measurements.

Figure 7 shows a times series trace of ground truth frame time alongside predicted frame time for an actual user trace run with the ME preset. Note that predicted follows ground truth reasonably well. Note also that the predicted frame time tends to be much more stable than the ground truth frame time. This is because the predicted frame time does not change as long as the POL is the same whereas the actual frame time can fluctuate rapidly based on the instantaneous client view. At first the player is in a simple environment with a small GPU load of about 1.3ms per frame. Then, after frame 167 he enters a more complex location where both actual and predicted frame times rise. In this location he encounters an explosion event near frame 657, which causes frame time to increase for about 102 frames. Then the values decrease back to 2ms per frame with a short drop to 1.2ms when the player has no complex objects in sight. At frame 1426 he enters a simple cave and the frame time drops to about 0.2ms.

Figure 8 illustrates how predicted SSIM also matches ground truth reasonably. Note that SSIM is plotted on an inverse log y-axis because the impact of a change close to one is much more important (from a psycho-perceptual perspective) than a change close to zero [8]. At frame 377, the player moves to a seaside location which has poor SSIM on ME. At frame 471 SSIM score rises as the player looks at a simple castle wall, but soon enough it drops again after he looks back at the sea. The player then runs towards the



(a) Online Profiling (b) Online Optimization

Figure 10: Per frame overhead of both profiling and optimization is low. Note that this is CPU time so it does not compete directly with GPU time.

castle gate where SSIM score is good enough until frame 818, when he enters a town. The player runs through it and goes back to the seashore at frame 1185.

To evaluate the overall accuracy, we compared actual and predicted data for four representative Fable locations each of which was encountered many times across multiple user traces: a typical town (Location 1), inside a house (Location 2), at a place with a panoramic view (Location 3) and inside a dungeon (Location 4). As seen in Figure 9, Location 1's frame time variance is relatively high. This is because Location 1 has a large quantity of small- and medium-weight graphical objects. Location 2 contains a modest quantity of small- and medium-weight graphical objects. Therefore, it still exhibits variance but its average frame time is lower than Location 1. Location 3 is different: there is a panoramic view with large objects that causes a heavy GPU load of 7ms per frame on average. The objects are visible everywhere, so the variance is not high. The prediction is therefore quite accurate. Location 4 is very small and simple, so frame time is really low. Due to its small number of objects, the prediction is also very accurate. Overall, the L1 estimation error is 15% and the L2 estimation error is 17%.

8.3 System Overhead

Since `dJay` is designed to operate on live instances in both profiling and optimization modes, it is important that the overhead of running `dJay` itself does not affect the frame time. Figure 10a shows the overhead of profiling, and Figure 10b shows the overhead of optimization. Profiling overhead is minimal at less than 0.6ms at the 99th percentile. This is much better than unfiltered profiling which has a cost of 8.9ms. Optimization overhead is similarly small at less than 2.8ms at the 99th percentile. Importantly, both of these costs are CPU costs, not GPU costs, and therefore do not impact the bottleneck resource.

8.4 Utility Maximization Benefits

We tested `dJay`'s utility optimization against the following baselines: *All HI*, *All ME* and *All LO*. Each of these baselines was statically provisioned for the corresponding preset regardless of the number of sessions or scene complexity.

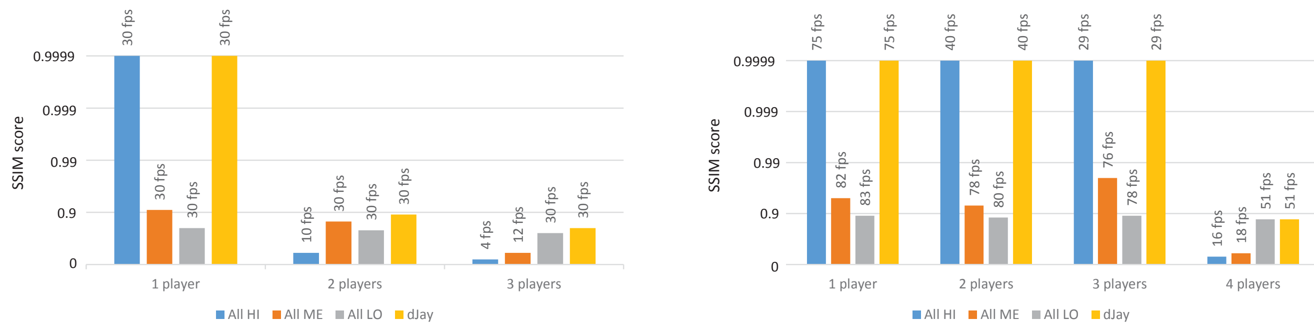
Increasing Multi-Tenancy: The first experiment simulates increasing server load with four players joining one by one. We show the results on Doom 3 and Fable 3 in Figure 11a and Figure 11b, respectively. The ground truth average SSIM per session is shown as we increase the number of sessions. The minimum observed frame rate is also reported. Note that the Doom 3 frame rate never goes above 30. This is due to an implementation artifact of our Doom 3 modifications, even for lightly loaded cases like a single player on LO. For Doom 3, when there was only one player, `dJay` sets the quality level of the instance to HI and therefore player's SSIM score was equal to 1, i.e. he observed the best possible quality. Then a second player joined, and HI stopped being the best option as it caused the FPS to drop below acceptable values. This impacted the SSIM too because even though renderings were still using the HI setting, the reduced rendering rate meant that stale frames often occurred, lowering SSIM. `dJay` switched one of the players to ME, so the average SSIM score not only became a better option than the low-FPS all-HI case, but also the all-ME case was surpassed due to a higher score of the player that was left on HI. With the third player joining, even the all-ME case could not keep a decent FPS, so `dJay`'s optimization led the player staying on HI to gradually drop to LO, while the ME player stayed on ME. This provided a better SSIM than any of the baselines. This case demonstrates an advantage of 3× tenant density of `dJay` over the HI static preset.

With Fable 3, HI preset worked well for one player. It even worked well for two and three players, though there was a drop in frame rate. However, the forth player caused a serious FPS drop if all the players stayed on HI, and even ME required too much GPU resources, so `dJay` switched all the players to LO. Despite the drop to LO, it was a much better option than HI or ME which could not provide a playable FPS.

It is useful to note that with both Fable 3 and Doom 3, even though profiling and regression model construction was conducted with master and slave pairs, the resulting model weights held up well when applied to higher densities of three and four simultaneous instances.

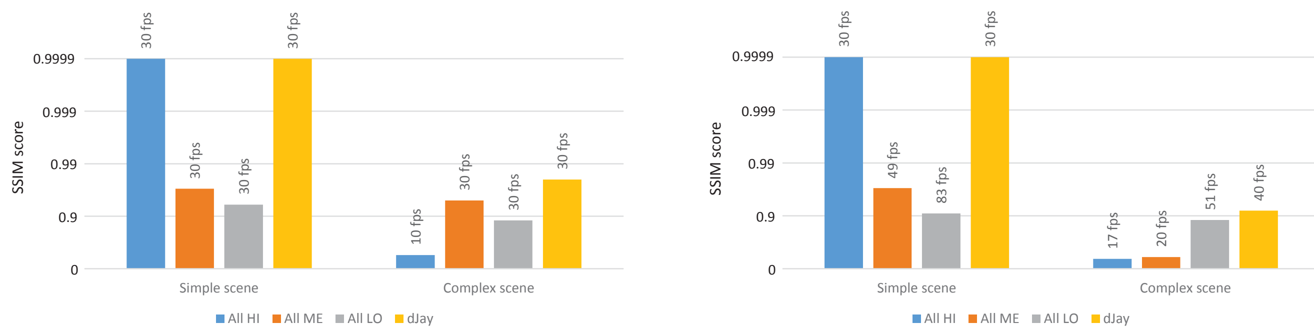
Increase Scene Complexity: The second test was designed to stress test an increase in server load by having one of the users go from a simple location to a visually richer location when the server is already at full capacity. The ground truth average session SSIM score is shown in Figure 12a and Figure 12b.

In the Doom 3 case, there were 2 players who could play on all the presets with 30 FPS, so `dJay` picked HI for them. After some time one of the players during his game progress entered a large room with a boss and minions which required a lot of GPU resources, so the server could not handle all of them on HI with an appropriate FPS. In this case `dJay`



(a) Doom 3 (b) Fable 3

Figure 11: Increasing Multi-Tenancy. SSIM score of `dJay` is always equal to or better than baselines. `dJay` also maintains at least 30 FPS whereas baselines can fall severely below acceptable FPS.



(a) Doom 3 (b) Fable 3

Figure 12: Increasing Scene Complexity. Again, SSIM score of `dJay` is always equal to or better than baselines. `dJay` also maintains at least 30 FPS whereas baselines can fall severely below acceptable FPS.

dropped him to ME and left other players on HI, so that their average SSIM score became higher than all the fixed preset cases.

In the Fable 3 case, there were 4 players who were assigned the HI preset because the server's performance was enough for them. One of the players finished his quest inside the house and went to the seashore where the game spawned additional scripted animations, so that his game process required more resources than were available on the server. If all of them kept playing on HI, they all would observe a very low FPS and a serious SSIM score drop as shown by the HI preset. `dJay` switched the GPU-heavy user to LO and left others on HI, which was better than switching all of them to LO. The performance tradeoff gained from one player was enough to keep the best visual quality for the others. This case demonstrated an advantage of 4× tenant density of `dJay` over HI and ME static presets.

High Load Responsiveness: Lastly, we zoom in on `dJay` under a high load situation. Figure 13 shows a case of two Fable 3 sessions with the aggregate load spiking above the 40ms Critical level starting at frame 131. As a result, `dJay` acts quickly to drop the load at frame 135. In this case, session 1 was downgraded from HI to LO.

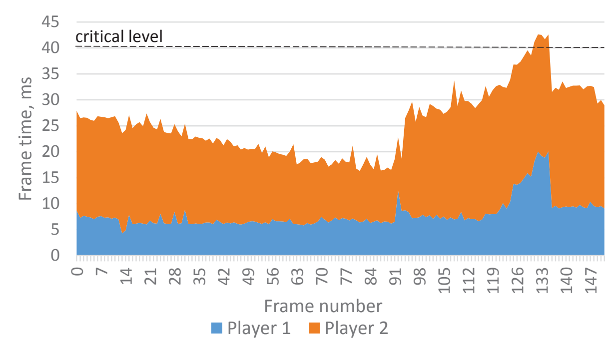


Figure 13: Responding quickly to high load minimizes poor frame time.

9. Related Work

Remote rendering is a classic idea (see, e.g., [14, 21]. Yet it was only recently that full remote execution of games on cloud infrastructure was embraced by companies like Sony (with their Playstation Now service), Amazon (with AppStream) and Nvidia (with their GRID service) as a way to deliver high-fidelity gaming experiences on mobile devices. A key challenge for cloud gaming products is managing the infrastructure costs. Anecdotal reports about the failure of OnLive's game streaming service blame the cost of their infrastructure, because they could only support one client per server. dJay has the potential to significantly reduce datacenter server costs by increasing the density of games executing on a single server.

Recent research on GPU virtualization provides an important building block to enable multi-tenant game execution on cloud servers. The simplest approach, often called pass-through, is to provide direct access to the GPU hardware from a guest VM. Such solutions prevent multiple VMs from accessing the hardware simultaneously. Early approaches to enabling 3D rendering capabilities inside a virtual machine focused on virtualization at the 3D API boundary: VMGL virtualizes the OpenGL v1.5 applications to run inside guest VMs with modest overhead [19]. VMware [11] describes their virtual GPU architectures that takes advantage of GPU hardware acceleration, rather than a pure emulation approach. Intel [25] describe a mediated pass-through solution to GPU virtualization, which allows multiple guest VMs to run a full featured GPU driver inside the guest VM, yet also enabling multiple guest VMs to access the same hardware.

The idea of adjusting game settings to control the load on the GPU was introduced in Kahawai [8], although in a very different setting. In Kahawai, the system runs a game using low quality settings on a low-power mobile GPU and runs the same game on a powerful GPU using high quality settings. In contrast with dJay, these settings are static and Kahawai does not address the problem of game server hosting density.

For non-GPU workloads, there is a large body of related works. Here, we simply describe a few representative systems. Increasing multi-tenant density for non-GPU workloads is a widely studied problem, and recent research efforts include library OSes [23] and OS containers [2, 24]. Many systems use consistent hashing for load distribution, in both data centers and wide-area distributed systems [5, 9, 16]. In big data analysis systems, SkewTune addresses issues of data load imbalance for mapreduce computations [18]. Schedulers for data center clusters have addressed fairness [15] and avoiding fragmentation and over-allocation [12].

10. Discussion and Limitations

dJay deals with managing sessions on a single server. One interesting avenue of further study concerns the related topic of global admission control and session-to-server assignment. Under what conditions should a client be assigned to a server? Which server in a cluster is best suited to handling a new client? When should a client request be rejected? In this work, we have made the simplistic assumption that the server can always at least meet 30 FPS at the lowest rendering setting for all sessions assigned to it, but clearly this decision is coupled with the overall service's session-to-server assignment policies. The profiling and optimization tools we have developed can lend insight into these questions higher up in the service provider stack.

One deceptively alluring solution to providing high quality graphics to all users all the time is to simply deploy luxury, maximum performance GPUs in the server. However, this overlooks two realities. First, the best price-for-performance GPUs are midrange. Luxury GPUs are expensive and therefore not a realistic option for service providers. Second, rendering demands have increased commensurate with GPU performance boosts for the past two decades. We cannot simply wait for Moore's law to provide free cycles because new rendering algorithms offering even better visual effects will likely be ready to use the new capacity.

Thus far we have used only a handful of rendering setting presets. For even more granular video quality control, it is also interesting to consider the space of all possible rendering settings. For example, Fable 3 presents at least eight dimensions for manipulating rendering settings (Table 2b). As dJay delves into more settings options, it needs commensurately more profiling trace data in order to build a model that accurately predicts each setting. While the exact data volume needed is an open question, we have shown that it is low overhead to collect more data online from active sessions.

While we have shown dJay working with two production games, future work includes extending dJay to a broader class of games, such as multiplayer and 2D. In a multiplayer setting, the GPU load induced by other players are still manifested as changes in the set of visible game objects. Therefore, dJay should still compute utilities appropriately. During profiling of a multiplayer game, updates from other players would need to be vectored to both master and slave. In addition, further game modifications would be needed in order to have only master (or only slave) send updates to other players. 2D games should be straightforward to support. Rather than modifying each game individually, it is appealing to consider implementing dJay as a game engine modification. Game engines such as Unity and Unreal already power the vast majority of games. The key dJay modifications (deterministic execution, exposure of AOL/POL and rendering setting changes) appear feasible at the game engine level.

11. Conclusion

From the perspective of a cloud gaming service provider, dJay lowers costs by achieving up to 4× better multi-tenant density over existing approaches. It takes advantage of the observation that dynamically changing rendering settings can help to achieve frame rate targets when under load. Moreover, by formulating the rendering settings assignment problem as utility-optimizing Multiple Choice Knapsack Problem, dJay provides optimal visual quality when resources are available.

References

[1] Amazon appstream. `http://aws.amazon.com/appstream`.

[2] Lxc. http://linuxcontainers.org.

[3] Nvidia grid cloud gaming. `http://shield.nvidia.com/grid`.

[4] Sony playstation now streaming. `http://us.playstation.com/playstationnow`.

[5] A. Adya, J. Dunagan, and A. Wolman. Centrifuge: Integrated lease management and partitioning for cloud services. In *NSDI*, 2010.

[6] M. Armbrust, A. Fox, R. Griffith, A. D. Joseph, R. Katz, A. Konwinski, G. Lee, D. Patterson, A. Rabkin, I. Stoica, and M. Zaharia. A view of cloud computing. *Commun. ACM*, 53(4):50–58, Apr. 2010.

[7] M. Claypool, K. Claypool, and F. Damaa. The effects of frame rate and resolution on users playing first person shooter games, 2006.

[8] E. Cuervo, A. Wolman, L. P. Cox, K. Lebeck, A. Razeen, S. Saroiu, and M. Musuvathi. Kahawai: High-quality mobile gaming using gpu offload. In *MobiSys*, May 2015.

[9] G. DeCandia, D. Hastorun, M. Jampani, G. Kakulapati, A. Lakshman, A. Pilchin, S. Sivasubramanian, P. Vosshall, and W. Vogels. Dynamo: Amazon's highly available key-value store. In *SOSP*, 2007.

[10] M. Deloura. *Game Programming Gems*. Charles River Media, Inc., Rockland, MA, USA, 2000.

[11] M. Dowty and J. Sugerman. Gpu virtualization on vmware's hosted i/o architecture. In *WIOV*, 2008.

[12] R. Grandl, G. Ananthanarayanan, S. Kandula, S. Rao, and A. Akella. Multi-resource packing for cluster schedulers. In *SIGCOMM*, 2014.

[13] S. Hollister. Onlive lost: how the paradise of streaming games was undone by one man's ego. `http://www.theverge.com/2012/8/28/3274739/onlive-report`, 2012.

[14] G. Humphreys, M. Houston, R. Ng, R. Frank, S. Ahern, P. D. Kirchner, and J. T. Klosowski. Chromium: A stream-processing framework for interactive rendering on clusters. In *Proceedings of the 29th Annual Conference on Computer Graphics and Interactive Techniques*, SIGGRAPH '02, pages 693–702, New York, NY, USA, 2002. ACM.

[15] M. Isard, V. Prabhakaran, J. Currey, U. Wieder, K. Talwar, and A. Goldberg. Quincy: Fair scheduling for distributed computing clusters. In *SOSP*, 2009.

[16] D. Karger, A. Sherman, A. Berkheimer, B. Bogstad, R. Dhanidina, K. Iwamoto, B. Kim, L. Matkins, and Y. Yerushalmi. Web caching with consistent hashing. In *WWW*, 1999.

[17] H. Kellerer, U. Pferschy, and D. Pisinger. *Knapsack Problems*. Springer Science and Business Media, 2004.

[18] Y. Kwon, M. Balazinska, B. Howe, and J. Rolia. Skewtune: Mitigating skew in mapreduce applications. In *SIGMOD*, 2012.

[19] H. A. Lagar-Cavilla, N. Tolia, M. Satyanarayanan, and E. de Lara. Vmm-independent graphics acceleration. In *VEE*, 2007.

[20] K. Lee, D. Chu, E. Cuervo, J. Kopf, Y. Degtyarev, S. Grizan, A. Wolman, and J. Flinn. Outatime: Using speculation to enable low-latency continuous interaction for cloud gaming. MobiSys 2015, May 2015.

[21] W. R. Mark, L. McMillan, and G. Bishop. Post-rendering 3d warping. In *Proceedings of the 1997 Symposium on Interactive 3D Graphics*, I3D '97, pages 7–ff., New York, NY, USA, 1997. ACM.

[22] S. Martello and P. Toth. *Knapsack Problems: Algorithms and Computer Implementations*. John Wiley & Sons, Inc., New York, NY, USA, 1990.

[23] D. E. Porter, S. Boyd-Wickizer, J. Howell, R. Olinsky, and G. Hunt. Rethinking the library os from the top down. In *ASPLOS*, 2011.

[24] D. Price and A. Tucker. Solaris Zones: Operating System Support for Consolidating Commercial Workloads. In *LISA*, 2004.

[25] K. Tian, Y. Dong, and D. Cowperthwaite. A full gpu virtualization solution with mediated pass-through. In *USENIX ATC*, 2014.

[26] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. Image quality assessment: From error visibility to structural similarity. *Trans. Img. Proc.*, 13(4):600–612, Apr. 2004.