Provision and use of GPU Resources for Distributed Workloads via the Grid

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Overview

- Motivation
- Integrating GPUs into your cluster. (It's really easy now)
- Using GPUs use cases at QM.
- Observations and discussion points.

Motivation

- GPUs are a commodity, programmable parallel architecture, ubiquitous as CPUs but offer significantly more parallel "streams".
- GPUs are significantly faster than CPU for appropriate problems and GPU optimised workflows often scale better when adding additional GPUs.
- GPU Performance (FLOPS) per watt is better than CPUs.
- GPUs Performance (FLOPS) per \$ is better than CPUs.





Deployment and Grid enabling GPUs

- of a GPU.
- jdl (GPU=1). CreamCE is being decommissioned.
- arcCE the is simplified by adding in arcce.conf to the subsection for the GPU queue

```
[queue:centos7 gpu]
```

 $\bullet \bullet \bullet$

 $\bullet \bullet \bullet$

```
slurm requirements= -gres=gpu:1 -n4
```

• Now all you have to do is submit a job to the centos7_gpu queue and you will get one GPU+4cores+12GB RAM.

• Deployment is really easy now, see backup fo details. We use SLURM where jobs get exclusive use

• Previously we enabled GPUs via a CreamCE with requirement that user had to request a GPU in the





IceCube

- Initial GPU deployment was driven by desire to support icecube.
- (https://sciencenode.org/feature/simulating-icecube-data-using-gpus.php)
- Have had both individual users (PhD students) and official grid production.
- Have yet to repeat for CentOS7.

• Why GPUs: Modelling photon propagation through ice. Light propagation is pretty much what is done in video games, so they started using GPUs. GPUs are doing a good job in photon simulation — up to 300 times faster than (single core ?) CPUs



Cern@school

- Cern@school Significant use of GPUs at QMUL for about a year.
- novel-cosmic-ray-detector).
- Using https://github.com/willfurnell/lucid-grid/ (Python 3 (Anaconda) with Tensorflow) for the actual particle detection.
- really is needed for Tensorflow use. Work done by pre university students.
- https://iopscience.iop.org/article/10.1088/1748-0221/13/10/C10004

 Uses CERN's Timepix detectors on the LUCID TechDemoSat-1 which launched in late 2014 (http:// www.sstl.co.uk/Blog/February-2013/TechDemoSat-1-s- LUCID—a-

Using the GPUs significantly sped up the workflow compared to using the CPU, and





- Deployment of AMBER and GROMACS on a GPGPU testbed of EGI by the MoBrain Competence Centre. Main use is for structural biology.
- Uses docker containers in udocker. udocker is a basic user tool to execute simple docker containers in user space without requiring root privileges.
- The only issue is that we regularly upgrade the kernel and NVIDIA drivers, so e.g DisVis and PowerFit application containers must be re-built with the corresponding NVIDIA driver in order to work in that site.
- NO Significant use of GPUs at QMUL. I think They really wanted GPUs in the cloud.

enmr







- Atlas have active group looking at GPU usage. Other LHC experiments have plans.
- Issue with using QMUL GPUs (CREAM CE need to set GPU=1 in the JDL). Should be simplified with ARC CE.
- Pre GDB on the subject https://indico.cern.ch/event/689511/
- Note even though deployment via containers using singularity we still need drivers and local libraries installed locally to access and use GPUs (CUDA + libcudnn).

LHC







Other Users

- Lots of individual HEP researchers using GPUs at home institutes. Some of this will end up needing to scale up on the grid.
- MoEDAL developing new methods using Machine learning (Tensorflow) to ID magnetic monopoles signatures in Nuclear track detectors (https://indico.cern.ch/ event/559774/contributions/2669803/attachments/1509702/2354134/ MachineLearningMonopolesAndMoedal.pdf).



Observations and Discussion Points

Anti Motivation

- Costs 5K per server + 6K for high end GPU.
- One high end GPU uses the same power as mid range duel socket server (300W).
- No point in buying GPU to speed up you work x10 if you only use it 1% of the time.
- "The GPU code gets a 200x speed improvement over a single CPU core". However my server has 64 Cores and costs half as much!
- Utilising the power of GPUs is hard parallel algorithms CPU Workflows to GPU workflows – performance pitfalls- even if using frameworks like tenserflow.
- Broad overview of GPU vs CPU impact: https://www.anandtech.com/show/14466/ intel-xeon-cascade-lake-vs-nvidia-turing





Not all GPUs are the same

	NVIDIA K40	NVIDIA V100	NVIDIA RTX 2080 SUPER	AMD MI60		
RAM	12GB ECC	32GB ECC	8GB	32GB ECC		
Memory badnwidth	288GB/s	900GB/s	496GB/s	1024GB/s	Just a perfo	asking fo rmance i
32bit(TFLOPS)	5	14	11.15	14.7	16/	/8 bit sup
64bit (TFLOPS)	1.68	7	0.349	7.4	64 bit si 8 bit	upport (c
16bit(TFLOPS)	N/A	28	22.3	29.5		
8bit (TFLOPS)	N/A	112	89.2	59		





Informed Choice

- Deep Learning, GPUs not always the right choice!
 - Convolutional networks and Transformers: Tensor Cores > FLOPs > Memory Bandwidth > 16-bit capability Recurrent networks: Memory Bandwidth > 16-bit capability > Tensor Cores > **FLOPs**
 - Rule of thumb. Here are some prioritisation guidelines for different deep learning architectures (https://timdettmers.com/2019/04/03/which-gpu-for-deep-learning/):
- 64bit (HPC/ simulation)
 - Enterprise GPUs (little choice here).

Notes consumer grade GPUs may not have the build quality to last intensive use.



Alternative Hardware

- Intel CPU chips AVX512, Deep Learning (DL)Boost (+Vector Neural Network Instruction (VNNI) set), bfloat16. Developing new discrete competitive GPUs.
- AMD GPUs/CPUs significant effort to develop ecosystem to enable and optimise AMD hardware (Radeon Instinct) in HPC (ROCm Platform) and open source projects (e.g. Tensorflow, Caffe).
- FPGAs (intel, Xilinx), Dedicated ASICs (Google TPUs, Intel Nervana NNP).
- But buying Nvidia is a safe bet but doesn't help develop competition.



Observations

- Further development of GPU resources will probably need dedicated funds. $\pounds/\$/$ €15K for a cheep GPU server (~3 compute servers / >200TiB usable storage).
- New Nvidia EULA of driver software prevents use of non enterprise GPUs (e.g. 1080Ti) in a "data centre". Can get research exception.
- Often see that CPU usage on our nodes are 100%. Posable limiting factor in making full use of GPU resources.
- We have significant performance difference not just between generations of GPUS (K40,P100,V100) but also for different types of calculations (8/16/32/64bit). Difficult for blind usage via pilot jobs.





Conclusions

- Deployment of GPUs on the grid is not hard. Getting them used is harder.
- Not all GPUs are the same. Different software require different balance of hardware features.
- Not yet clear what the workload/workflow will be. Will impact hardware choices (esp HL-LHC).
- Hardware development and related software support is in flux.
- HEP needs to move from "what can we do" on GPUs to "what should we do".
- No accounting in APEL for GPUs.
- What do grid sites do? Chicken and egg problem, sources of funding for GPUs.



Backup

Obtaining 1st GPU

- Recycled desktop workstation capable of powering a GPU (top end GPU requires ~300W on top of existing CPU... + right connector 2*PCIe 8pin)
- Obtained Free GPU from NVIDIA GPU Grant
 Program (e.g. <u>https://</u> <u>developer.nvidia.com/</u> <u>academic_gpu_seeding</u>).



Dell T5500 Workstation + Nvidia K40c GPU

Obtaining Cheap GPUs

- Buy a gaming GPU.
- 1* NVIDIA 1080 Ti founders edition. Dell Alienware Aura 2017
- Brought "off the shelf" Dell Alienware PC. Able to buy via a framework agreement and get delivery in <10days (good for end of financial year).
- Be careful Nvida has restrictions on use of consumer GPUs in data centres. Research exceptions available.



- Brought HPE server + Enterprise GPUs (K80s).
- Funded through money down "the back of the sofa"
- Nvidia+CUDA dominate the market so little point buying others YET.

Obtaining more GPUs





HPE DL380 + 2* Nvidia K80s (~4* K40)



- https://docs.nvidia.com/cuda/cuda-installation-guide-linux/index.html
- Physically install a GPU and test that the kernel see it
 - lspci | grep -i nvidia
 - 01:00.0 3D controller: NVIDIA Corporation GK110BGL [Tesla K40c] (rev a1)
- Install the CUDA repo, install CUDA and reboot (this should install drivers).
 - yum install cuda gcc kernel-devel-\$(uname -r) kernel-headers-\$(uname -r)
- Run "nvidia-smi" to check GPU is available.
- Enable persistence of driver state across CUDA job runs (driver stay loaded).
 - systemctl [start|enable] nvidia-persistenced
- Install the CUDA Deep Neural Network library for tensor support
 - yum install libcudnn7-7.4.1.5-1.cuda10.0.x86 64
- compile and run the test program
 - cp -r /usr/src/cudnn_samples_v7/ \$HOME
 - cd \$HOME/cudnn_samples_v7/mnistCUDNN
 - make clean && make
 - ./mnistCUDNN

System Deployment



SLURM Batch System Deployment

- - GresTypes=gpu
 - •
 - CoresPerSocket=4 ThreadsPerCore=2 State=UNKNOWN
 - •
 - Default=NO MaxTime=99:00:00 State=UP
- In /etc/slurm/gres.conf
 - NodeName=cn291 Name=gpu Type=teslaK40 File=/dev/nvidia0
- for a user)
 - ConstrainDevices=yes
- Submit jobs: sbatch --gres=gpu:1 -n1 test_gpu.sh

• Modify slurm to enable support for Generic resource (GRES), e.g. in /etc/slurm/slurm.conf

NodeName=cn291 CPUs=8 Gres=gpu:teslaK40:1 RealMemory=31911 Sockets=1

PartitionName=centos7 gpu Nodes=cn291 MaxMemPerCPU=20480 DefMemPerCPU=12288

• cgroups for slurm should be enabled and in /etc/slurm/cgroup.conf (set exclusive use of a GPU)

Integrate with SGE • Create host complex : qconf -mc shortcut type #name urgency # • • • INT YES YES <= gpu gpu • • •

Add complex attribute to host: qconf -me cn291 igodol

hostname	cn291.htc.es
load_scaling	NONE
complex_values	gpu=1
user_lists	NONE
xuser_lists	NONE
projects	NONE
xprojects	NONE
usage_scaling	NONE
report_variables	NONE

Submit job: qsub -l gpu=1 testgpu.job

relop requestable consumable default



sc.qmul

