# Measuring Energy Consumption with the Energy Measurement Library

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# Outline

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**Classification of measurement tools**

- External devices
- Intranode devices
- Hardware counters

**Some examples**

- Power meters
- Metered power distribution units (PDUs)

## Advantages

- No overhead

## Disadvantages

- Coarse system-level data

# Intranode Devices

Highly customized tools that measure energy within a node

## Some examples

- Linux Energy Attribution and Accounting Platform ($LEA^2P$)
- PowerMon2
- PowerPack

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# Intranode Devices

## Advantages

- More accurate (per-component) data

## Disadvantages

- Scalability
- Cost

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# Hardware Counters

Hardware providing consumption data through an API

## Some examples

- Nvidia Management Library (NVML)
- Intel Running Average Power Limit (RAPL)
- Intel Manycore Platform Software Stack (MPSS)

### Advantages

- Abstraction
- Simplicity
- Precision

### Disadvantages

- Not always available
- **Heterogeneous interfaces**

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# Heterogeneous interfaces

**Every tool has its own:**

- Software interface
- Choice of metric (power/energy)
- System of units
- Adequate sampling rate

Standards are needed!

# Performance API (PAPI)

...why not read energy events from PAPI?

# Performance API (PAPI)

~~...why not read energy events from PAPI?~~ (they didn't exist)

# Performance API (PAPI)

Can now access some hardware energy counters

**Limitations**

- Scope limited to hardware counters
- Lower-level abstraction

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EML abstracts away tool-specific details

- Specific software interface calls
- Quantity reported (instant power vs cumulative energy)
- Units reported
- Sampling rate

It also provides convenient data acquisition and exporting

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# Goals

- Portable instrumentation
- Convenient data acquisition
- Low overhead
- Easy to extend
- Open source

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EML was first implemented as a C++ library based on the factory method pattern

**Shortcomings**

- No device discovery functionality
- C code difficult to instrument

# Current Implementation

EML has been rewritten in C and many issues addressed

**Additions**

- Run-time autodetection of supported measurement devices
- Further simplified model
- JSON exporting of raw measurement data
- Open sourced under the GPL

`https://github.com/hpc-ull/eml`

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# Current Implementation

**Initial device support**

- Intel CPUs Sandy Bridge and later (through Intel RAPL)
- Intel Xeon Phi from the host (through Intel MPSS 3.x)
- Nvidia Fermi and Kepler cards (through NVML)

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# Abstraction Model

- Stopwatch-like instrumentation of relevant code sections
- Launches data gathering threads
- C-style encapsulation (opaque types with related functions)

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# Basic Usage

```c
#include <eml.h>
#include <stdlib.h>

int main() {
  emlInit();
  //get total device count and allocate result handles
  size_t count;
  emlDeviceGetCount(&count);
  emlData_t* data[count];

  emlStart();
  //...do work...
  emlStop(data);
  //...use data...
  emlShutdown();
}
```

# Data Acquisition

```
for (size_t i = 0; i < count; i++) {
  double consumed, elapsed;
  emlDataGetConsumed(data[i], &consumed);
  emlDataGetElapsed(data[i], &elapsed);
  emlDataFree(data[i]);

  //query each device name to print it alongside results
  emlDevice_t* dev;
  emlDeviceByIndex(i, &dev);
  const char* devname;
  emlDeviceGetName(dev, &devname);
  printf("%s: %gJ in %gs\n", devname, consumed, elapsed);
}
```

# Nested Measurements

```
emlStart();
for (int i = 0; i < N; i++) {
  emlStart();
  //...do work...
  emlStop(inner_data[i]);
}
emlStop(outer_data);
```

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**Node**

- 2 x Intel(R) Xeon(R) @ 3.20GHz (Sandy Bridge)
- 8 Cores each
- 20MB L3 cache
- 64GB RAM
- gcc 4.4.5-8
- Intel MSR RAPL Interface

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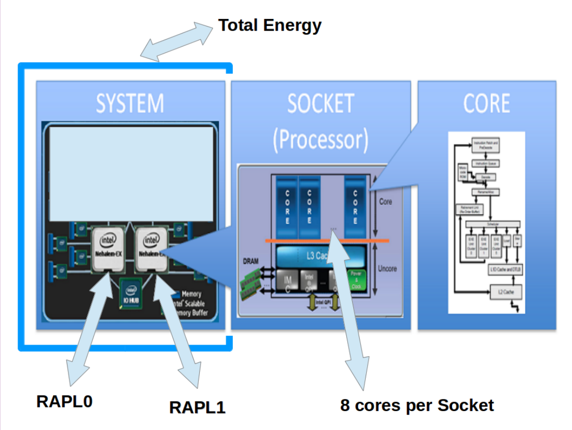
# Sandy Bridge Measurements

## Performed Experiments



# The *Bejeque* Cluster

## GPU

- 1 x Nvidia Tesla M2090
- 512 cores @ 1.3 GHz
- 6 GB of GDDR5 Memory
- CUDA 4.1
- NVML interface

# Methodology

## Instrumented applications

- OSU Microbenchmarks for communication overhead
- Matrix multiplication implementations
  - Sequential
  - OpenMP
  - CUDA shared memory arrays
  - CUDA global memory

# Methodology

## Process

1. Code was instrumented with EML calls
2. Both instrumented and non-instrumented versions executed through *eml-consumed*
   - wrapper reporting a command's consumption similar to the Unix *time* command

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# Sequential and OpenMP Matrix Multiplication

## Instrumented code for the Sandy Bridge experiments

```
#include <omp.h>
#include <eml.h>

void matmul_omp(float *C, float *A, float *B, int N) {
  int i, j, k;

  #pragma omp parallel for private(j,k) shared(A,B,C,N)
  for(i = 0; i < N; i++)
    for(j = 0; j < N; j++)
      for(C[i*N+j] = 0.0, k = 0; k < N; k++)
        C[i*N+j] += A[i*N+k] * B[k*N+j];
}
```

# Sequential and OpenMP Matrix Multiplication

```
int main(int argc, char *argv[]) {
  // ... Matrix initialization ...
  size_t count;
  emlInit();
  emlDeviceGetCount(&count);
  emlDevice_t* devices[count];
  emlData_t* data[count];

  emlStart(); // EML Measurement Start
  matmul_omp(C, A, B, N); // Matrix Mult
  emlStop(data); // EML Measurement Stop

  // ... Data postprocessing ...
  emlShutdown();
  return 0;
}
```

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## Instrumented code for the CUDA experiments

```
#include "common.h"
#include "matrix_common.h"
#include <eml.h>

__global__
void matmul_kernel(float *C, float *A, float *B, int N) {
  int i = blockIdx.y * blockDim.y + threadIdx.y;
  int j = blockIdx.x * blockDim.x + threadIdx.x;

  if((i<N) && (j<N))
  {
    C[i*N+j] = 0;
    for(int k = 0; k < N; k++)
      C[i*N+j] += A[i*N+k] * B[k*N+j];
  }
}
```

# CUDA Matrix Multiplication

```
int main(int argc, char *argv[]) {
  // EML Preparation
  size_t count;
  emlInit();
  check_error(emlDeviceGetCount(&count));
  emlDevice_t* devices[count];
  emlData_t* data[count];

  // .. Matrix and CUDA Initialization ..

  emlStart();
```

# CUDA Matrix Multiplication

```
// Memory allocation
HANDLE_ERROR(cudaMalloc(&d_A, bytes));
HANDLE_ERROR(cudaMalloc(&d_B, bytes));
HANDLE_ERROR(cudaMalloc(&d_C, bytes));
// Host initializing
Initialize(A, N*BLOCK_SIZE, N*BLOCK_SIZE);
Initialize(B, N*BLOCK_SIZE, N*BLOCK_SIZE);
// Device initializing
HANDLE_ERROR(cudaMemcpy(d_A, A, bytes,
    cudaMemcpyHostToDevice));
HANDLE_ERROR(cudaMemcpy(d_B, B, bytes,
    cudaMemcpyHostToDevice));

dim3 dimBlock(BLOCK_SIZE, BLOCK_SIZE);
dim3 dimGrid(N, N);
```

# CUDA Matrix Multiplication

```
matmul_kernel<<<dimGrid, dimBlock>>>(d_C, d_A, d_B,
    N*BLOCK_SIZE);

HANDLE_ERROR(cudaMemcpy(C, d_C, bytes,
    cudaMemcpyDeviceToHost));

// EML Measurement Stop
emlStop(data);

// .. Data Retrieving and memory deallocation ..
emlShutdown();

return 0;
}
```

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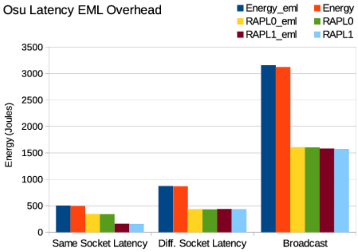
# Communication Experiments

## Performed Experiments

- Point to point communication (*osu_latency*)
- Broadcast (*osu_bcast*)

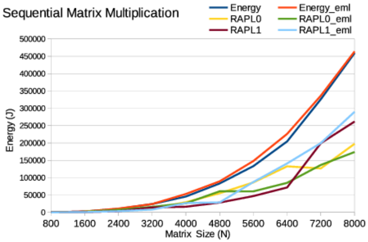



- Comparison between instrumented and non instrumented versions
- Energy 1.53% higher for instrumented same socket latency
- Energy 0.60% higher for instrumented different socket latency
- Energy 1.09% higher for instrumented broadcast

### Performed Experiments

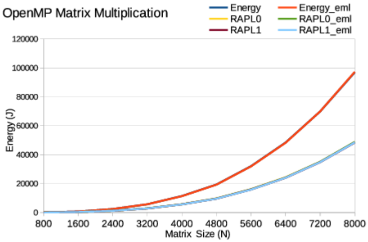
- Sequential Matrix Multiplication
- OpenMP Matrix Multiplication

# Sequential Matrix Multiplication




- Not very precise due to RAPL limitations
  - Matrix Multiplication uses 1 core
  - RAPL measures the entire socket
- Energy up to 10.59% higher for instrumented matrix multiplication

# OpenMP Matrix Multiplication



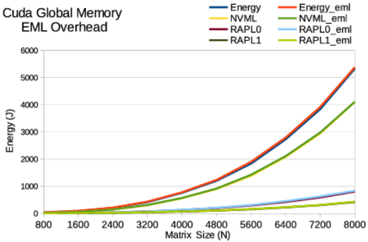

- Very precise due to RAPL nature
  - Matrix Multiplication uses 16 cores
  - RAPL measures the entire sockets
- Energy up to 0.81% higher for instrumented matrix multiplication

**Performed Experiments**

- Global Memory Matrix Multiplication
- Shared Memory Matrix Multiplication

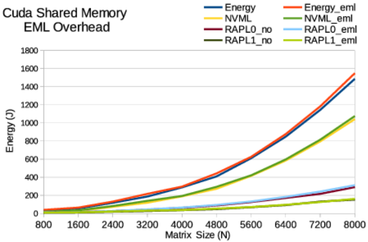
The executions are example codes provided by Nvidia instrumented with EML

# Global Memory Matrix Multiplication




- Constant energy overhead due to NVML calls
- Energy up to 9.53% higher for very low size problems (Absolute error, 9 Joules)
- Energy 0.99% higher for size of 8000 rows

# Shared Memory Matrix Multiplication




- Same constant energy overhead due to NVML calls
- Energy up to 15.98% higher for very low size problems (Absolute error, 9 Joules)
- Energy 0.52% higher for size of 8000 rows

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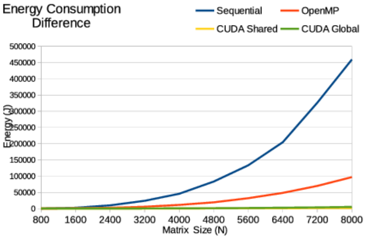


- Sequential energy consumption is not comparable. Lack of precision.
- CUDA Examples consume much less than Sandy Bridge versions
- Cuda Shared memory is the less energy consuming $(1487, 24J\ N = 8000)$

# Outline

# Conclusions

- EML is a practical tool for energy consumption analysis
- Low enough overhead to fulfill its role

# Future Work

- Support for more devices (including out-of-node)
  - Metered PDUs
  - Instrumented mobile targets
- Integration with interposition techniques
- Complementary data postprocessing tools

# THANKS

https://github.com/hpc-ull/eml

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