

Motivation

Democratize LLMs for HPC community

- Creation of reliable, highly specialized and optimized AI assistants across major HPC components: Programing Models, I/O, Math Libraries, Tooling, and beyond
- Production of high-quality software with level of trustworthiness of up to 90% higher than OpenAI ChatGPT-4o

A Reliable and Efficient Ecosystem

Based on robust and open-source tools

- Code Llama 7B parameter fine-tuning, LoRA, and Pytorch
- Low computational requirements
- Code Llama (13GB), AI-Assistant (~100MB), training/testing data (~KB)
- The creation of AI-assistants takes in order of a few minutes (< 15 min) on 2x NVIDIA GPUs

ChatHPC Library

Accelerating AI assistants (LLMs) production for HPC

- An easy-to-use front-end Python library for AI assistants' creation and testing focus on data quality

ChatHPC CLI:

```
$ chatnpc train # Finetune the assistant.
$ chatnpc verify # Verify the assistant on training set.
$ chatnpc test # Test the assistant on unseen data.
$ chatnpc run # Interactively run the assistant.
```

Interactive run session:

```
$ chatnpc ()> /context
Context: Introduction to Kokkos
$ chatnpc (Introduction to Kokkos)> What is LayoutLeft?
LayoutLeft refers column-major layout where consecutive entries in
the same column of a 2-D array are contiguous in memory.
```

Fine-Tuning and Testing

Supervised by HPC experts

- Fine-tuning consists of a JSON or YAML file with a collection of question-context-answer tuples
- Testing data must be different to training (fine-tuning) data. Expected answers can be added as part of the testing data for fast testing using ChatHPC

```
{
  "question": "Can you translate this HIP code to Kokkos?",
  "global__ void stencil (int n, float dx, float dy, float *u,
    float *u_new, float *f) {
    int i = blockIdx.x * blockDim.x + threadIdx.x;
    int j = blockIdx.y * blockDim.y + threadIdx.y;
    if (i > 0 && i < n-1 && j > 0 && j < n-1) {
      u_new[i][j] = 0.25 * (u[i-1][j] + u[i+1][j] +
        + u[i][j-1] + u[i][j+1]) + f[i][j];
    }
  },
  "context": "HIP to Kokkos translation",
  "answer": "Kokkos::parallel_for (' stencil',
    Kokkos::MDRangePolicy<Kokkos::Rank<2>>
    ({1, 1}, {n-1, n-1}),
    KOKKOS_LAMBDA(const int i, const int j) {
      u_new[i][j] = 0.25 * (u[i-1][j] + u[i+1][j] +
        + u[i][j-1] + u[i][j+1]) + f[i][j];
    });",
  "...
}
```

Evaluation

Elevating LLM capabilities for HPC targets

- We measure the performance of the AI assistants as the percentage of the prompts within testing data sets that were answered correctly

ChatHPC AI Assistant	Code Llama	Initial	Refinement	ChatGPT 4o
ChatHPC for Kokkos	7.34%	77.51%	85.75%	48.34%
ChatADIOS2	0.00%	40.87%	100.00%	25.00%
ChatMAGMA	0.00%	44.26%	94.93%	0.00%
ChatIRIS	0.00%	87.29%	-	35.00%
ChatPORT	2.54%	20.00%	76.00%	79.66%

Impacting correctness with more data

ChatHPC AI Assistant	Extra Training Data used for Refinement	Correctness
ChatHPC for Kokkos	12.33%	17.77%
ChatADIOS2	37.50%	62.85%
ChatMAGMA	51.72%	53.37%
ChatPORT	77.27%	76.68%

ChatHPC Design: How to use it?

ChatHPC Library

(I) Base Model (Code Llama)

(1) Fine-Tuning

(A) Training Data

(II) ChatHPC Model

Merge Model + Adapters

(B) AI Assistants (Adapters)

ChatHPC for Kokkos

ChatIRIS

ChatPort

ChatADIOS2

ChatMAGMA

ChatTAU

Programming Systems

I/O

Math Libraries

Performance Profilers

Expert-in-the-loop

(2) Testing

(C) Testing Data

(D) Learning Gaps

(3) Refinement (Fine Tuning)

(A) Training Data

(E) Refinement Data

3 easy steps

- Fine-tuning**
AI assistant creation
- Testing**
Identify learning gaps
- Refinement**
Filling learning gaps + fine tuning

<https://code.ornl.gov/ChatHPC/ChatHPC-project>

ChatHPC for Kokkos: An AI Assistant for the C++ Kokkos Portable Front-End

5 contexts/capabilities

- Documentation
- Installation
- Development
- Parallelization
- Translation/Portability
OpenMP/ACC, CUDA, HIP

Context	Code Llama	ChatHPC for Kokkos (Initial)	ChatHPC for Kokkos (Refinement)	ChatGPT (4o)
Documentation	9.50%	89.00%	-	81.00%
Installation	27.20%	78.00%	-	45.50%
Development	0.00%	85.00%	-	15.14%
Parallelization	0.00%	45.00%	90.90%	66.70%
Translation	0.00%	55.58%	85.85%	33.40%
OpenACC*	0.00%	53.20%	87.20%	41.30%
CUDA*	0.00%	58.70%	83.50%	31.20%

*No OpenACC and CUDA code used for fine-tuning

Translate the next CUDA code to Kokkos

```
__global__ void sdot(int n, float *x, float *y, float *result) {
  int i = threadIdx.x + blockIdx.x * blockDim.x;
  float update = 0.0;
  if (i < SIZE) {
    update = x[i] * y[i];
    atomicAdd(result, update);
  }
}
```

Chat for Kokkos output:

```
Kokkos::parallel_reduce(SIZE,
  KOKKOS_LAMBDA(int i, float &update){
    update += x(m) * y(m);
  },
  Kokkos::Sum<float>(result));
```

3x10⁵ speedup on AI convolution

3x10³ Speedup on DOT product
Competitive w.r. t. cuBLAS

Acknowledgments

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ChatIRIS: Taskification of HPC Applications Using IRIS

- IRIS is a portable task-based runtime for extreme heterogeneous systems
- ChatIRIS: Assist developers in the taskification of OpenMP, CUDA and HIP applications using IRIS
- No need of refinement

Translate the next CUDA code to IRIS:

```
alpha = 2.0;
X = (float *) malloc(SIZE * sizeof(float));
Y = (float *) malloc(SIZE * sizeof(float));
Z = (float *) malloc(SIZE * sizeof(float));
for (int i = 0; i < SIZE; i++) { X[i] = i; Y[i] = i; }
cudaMalloc((void **)&d_x, SIZE * sizeof(float));
cudaMalloc((void **)&d_y, SIZE * sizeof(float));
cudaMalloc((void **)&d_z, SIZE * sizeof(float));
// Initialization of arrays
cudaMemcpy(d_x, X, SIZE * sizeof(float), cudaMemcpyHostToDevice);
cudaMemcpy(d_y, Y, SIZE * sizeof(float), cudaMemcpyHostToDevice);
int blocks = floor(SIZE / threads) + 1;
saxpy<<blocks, threads>>(alpha, d_x, d_y, SIZE);
cudaDeviceSynchronize();
sdot<<blocks, threads>>(d_x, d_x, SIZE);
cudaFree(d_x);
cudaFree(d_y);
cudaFree(d_z);
free(X);
free(Y);
free(Z);
```

*No HIP code used for fine-tuning

Context	Code Llama	ChatIRIS	ChatGPT 4o
Documentation	0.00%	95.00%	70.00%
OpenMP -> IRIS task code	0.00%	82.00%	10.00%
CUDA -> IRIS task code	0.00%	90.00%	50.00%
HIP -> IRIS task code*	0.00%	81.66%	10.00%

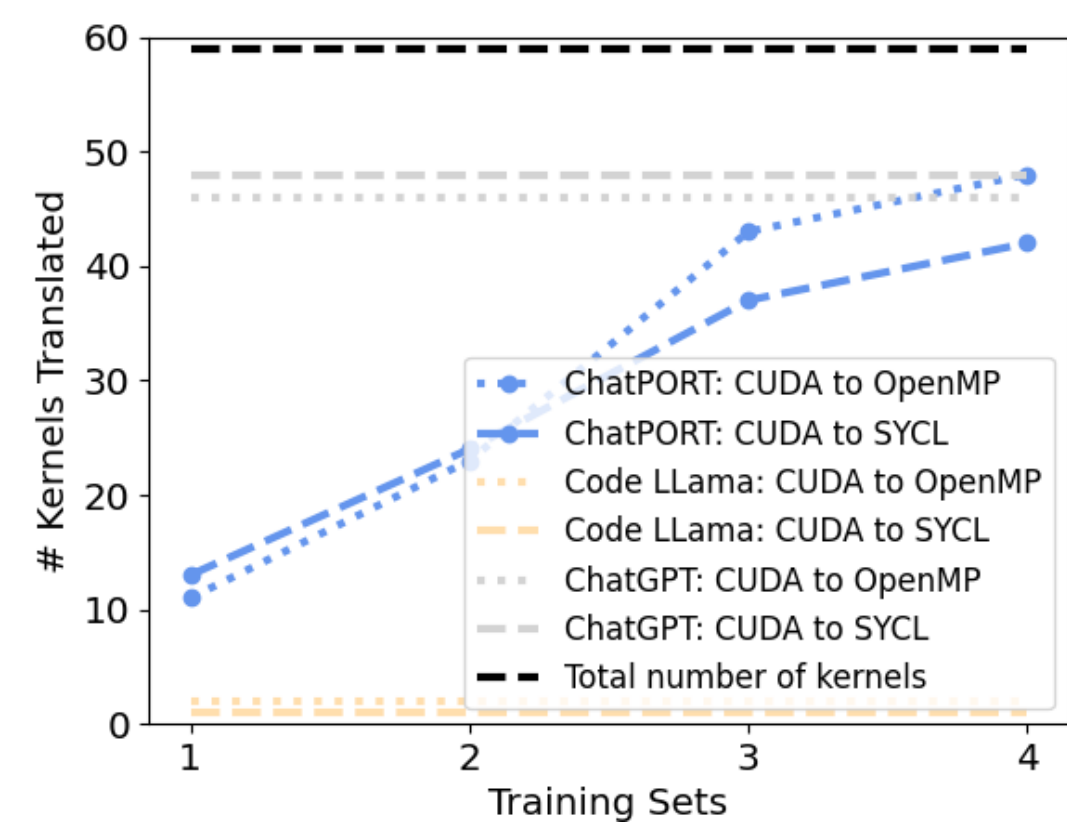
ChatIRIS output:

```
// Architecture-agnostic IRIS task code
alpha = 2.0;
iris_init(&argv, 1);
iris_mem iris_x;
x = (float *) malloc(SIZE * sizeof(float));
iris_data_mem_create(&iris_x, x, SIZE * sizeof(float));
iris_mem iris_y;
y = (float *) malloc(SIZE * sizeof(float));
iris_data_mem_create(&mem_y, Y, SIZE * sizeof(float));
iris_mem iris_z;
z = (float *) malloc(SIZE * sizeof(float));
iris_data_mem_create(&mem_z, z, SIZE * sizeof(float));
// Initialization of arrays
iris_graph graph;
iris_graph_create(&graph);
iris_task saxpy_task;
iris_task sdot_task;
iris_task_create(&saxpy_task);
iris_task_create(&sdot_task);
void saxpy_params[3]={&alpha, &iris_x, &iris_y};
int saxpy_params_info[3]={sizeof(A), iris_w, iris_r};
saxpy_params, saxpy_params_info);
void sdot_params[2]={&iris_x, &iris_x};
int sdot_params_info[2]={iris_w, iris_r};
iris_task_kernel(task, "sdot", 1, NULL, &SIZE, NULL, 2,
sdot_params, sdot_params_info);
iris_graph_task(graph, saxpy_task, iris_default, NULL);
iris_graph_task(graph, sdot_task, iris_default, NULL);
iris_graph_submit(graph, iris_any, 1);
free(X);
free(Y);
free(Z);
iris_finalize();
```

ChatPORT: Porting CUDA to SYCL/OpenMP Offloading for HPC Kernels

- ChatPORT uses benchmarks from HecBench with hundreds of kernels implemented in CUDA, HIP, SYCL and OpenMP Offloading
- ChatPORT provides competitive performance w.r.t. ChatGPT 4o using only 22 kernels for fine-tuning

Training Set	#Kernels	Benchmark (kernel) used
1	5	accuracy, geodesic, lr, maxpool3d, perplexity
2	10	damage, knn, heat2d, laplace3d, md
3	15	advCubatureHex3D, backprop, channelShuffle, lr, meanshift
4	22	chemv, clenergy, pathfinder, pointwise, swish, stddev, tissue



ChatMAGMA: Porting HPC Applications to MAGMA

- MAGMA is a portable and heterogeneous BLAS/LaPACK library for Intel/NVIDIA/AMD accelerators
- ChatMAGMA assists application developers in the porting of vendor-specific BLAS/LaPACK
- codes (codes using Intel MKL, NVIDIA cuBLAS and cuSolver, or AMD hipBLAS and hipSolver) to MAGMA library
- High level of trustworthiness w.r.t. Code Llama (no fine-tuning) and ChatGPT 4o
- Fine-tuning time less than 10 min. on 2x NVIDIA GPUs
- This work was made in honor of **Stan Tomov**, father of the MAGMA library



Translate the next NVIDIA cuSolver code to MAGMA:

```
// NVIDIA cuSolver (GPU-only) dgstrf code
int lwork=0;
double *dwork;
int *dipiv;
double *dinfo;
cusolverDnHandle_t handle;
cusolverDnCreate(&handle);
double *hA=(double *) malloc(n*n*sizeof(double));
cusolverDnDgetrf_bufferSize(handle, n, n, dA, n, &lwork);
cudaMalloc((void **)&dA, n*n*sizeof(double));
cudaMalloc((void **)&dwork, sizeOf(double)*lwork);
cudaMalloc((void **)&dipiv, n*sizeof(int));
cudaMalloc((void **)&dinfo, sizeof(int));
cudaMemcpy(dA, hA, n*n*sizeof(double), cudaMemcpyHostToDevice);
cusolverDnDgetrf(handle, n, dA, n, dwork, dipiv, dinfo);
cudaMemcpy(hA, dA, n*n*sizeof(double), cudaMemcpyDeviceToHost);
cudaFree(dA);
cudaFree(dwork);
cudaFree(dipiv);
cudaFree(dinfo);
free(hA);
cusolverDnDestroy(handle);
```

ChatMAGMA output:

```
// MAGMA (CPU+GPU) dgstrf code
magma_queue_t queue;
magma_device_t cdev;
magma_get_device(&cdev);
magma_queue_create(cdev, &queue);
double *hA;
magmaDouble_ptr dA;
magma_int_t *ipiv;
magma_int_t info;
magma_dmalloc_cpu(&hA, n*n);
magma_dmalloc(&dA, n*n);
magma_imalloc_cpu(&ipiv, n);
magma_dsetmatrix(n, n, hA, n, dA, n, queue);
magma_dgetrf_gpu(n, n, dA, n, ipiv, &info);
magma_dgetmatrix(n, n, dA, n, hA, n, queue);
magma_free(dA);
magma_free_cpu(hA);
magma_free_cpu(ipiv);
magma_queue_destroy(queue);
```

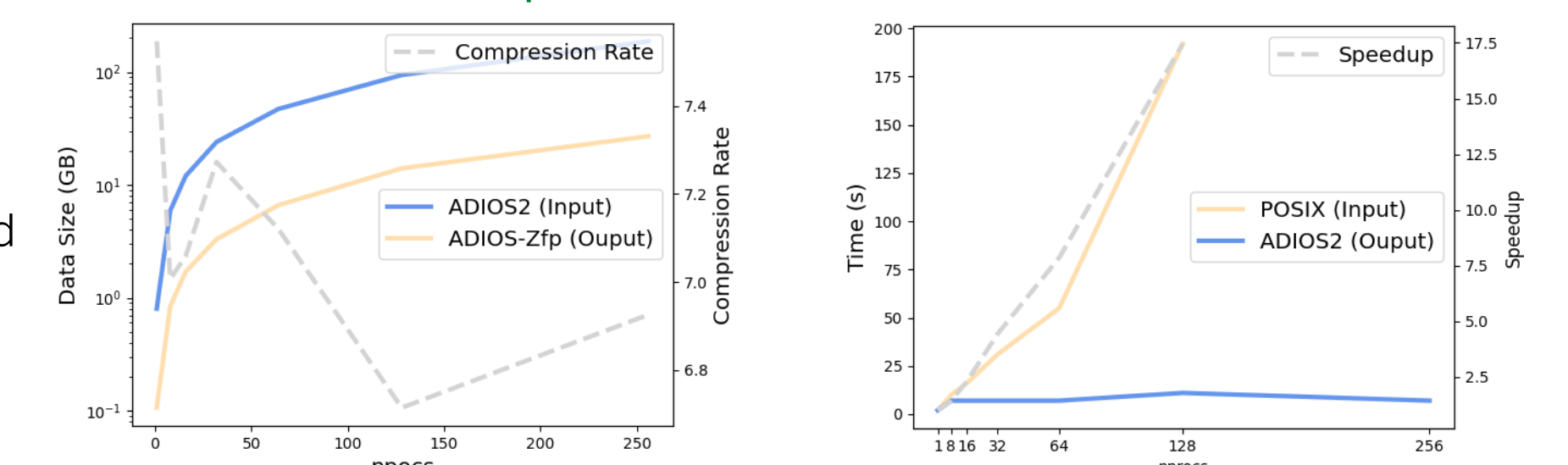
*No AMD hipBLAS or hipSolver code used for fine-tuning

Context	Code Llama	ChatMAGMA (Initial)	ChatMAGMA (Refinement)	ChatGPT (4o)
Intel MKL	0.00%	37.50%	93.00%	0.00%
NVIDIA cuBLAS/cuSolver	0.00%	50.00%	96.50%	0.00%
AMD hipBLAS/hipSolver*	0.00%	45.30%	95.30%	0.00%

ChatADIOS2: HPC I/O for Applications using ADIOS2

- ADIOS2 is a C++ library to enable HPC writes to parallel file systems and in-memory communication
- ChatADIOS2 assist developers with ADIOS2 documentation, definition of ADIOS2 variables, data compression and parallelization

High scalability and speedup on ORNL's Frontier for parallel I/O and data compression



Context	Code Llama	ChatADIOS2 (Initial)	ChatADIOS2 (Refinement)	ChatGPT (4o)
Introduction	0.00%	77.00%	100.00%	33.00%
Variable Definition	0.00%	50.00%	100.00%	33.00%
Data Compression	0.00%	25.00%	100.00%	0.00%
Parallelization	0.00%	0.00%	100.00%	100.00%

Future Work: Facing the Challenges

Towards a fully AI-Assisted HPC Ecosystem

- Expand on fine-tuning using larger windows for longer codes
- Elevate trustworthiness levels
- Agentic AI for a better HPC-AI interoperability
- LLM multi-modality for HPC targets

Observations

- Fine-tuning:** We demonstrated the effectiveness of finetuning pretrained and relatively small LLMs (7-billion parameter Code Llama model) by using expert-supervised data as a cost-effective approach to rapidly creating trustworthy HPC capabilities with high levels of correctness
- Self-learning:** Because of the recurring repetitive patterns found in multiple HPC cases, AI assistants can learn new capabilities, such as portability of AMD math libraries (ChatMAGMA), translation of CUDA or HIP codes (ChatHPC for Kokkos and ChatIRIS), or N-dimensional data definition (ChatADIOS2), without being provided specific training data for those cases, thereby reducing the required size of the training datasets
- Expert-in-the-loop:** Performance of AI assistants improves considerably when human expertise is integrated into the fine-tuning process to create the training data and identify learning gaps, although experts may not be always available
- Accessibility:** ChatHPC infrastructure is accessible to everyone and requires only modest computational resources (a few minutes on a node with two NVIDIA GPUs). Also, we demonstrated that the data required for users to create new capabilities is relatively small
- Impact on HPC:** Apart from elevating the productivity of HPC software by using AI assistants in critical tasks (parallelization, portability, optimization, scalability, and instrumentation), the AI assistants can optimize codes from those passed as input to achieve important speedups (of up to 300x) and scalability improvements (of up to 17.5x) for different domains
- Leveraging HPC efforts:** ChatHPC benefits from the important efforts made by the HPC community in the past decade to provide highly productive and portable solutions (e.g., Kokkos, ADIOS2), and the code transformations made by the AI assistants provide the capabilities (scalability, speedup, portability) that modern HPC requires.