

My goal is to build **programming languages, compilers, and runtime systems** for efficient and secure **AI systems** that make it easy to develop and deploy end-to-end AI pipelines on large-scale *distributed* clusters, while utilizing *heterogeneous* architectures.

Distributed and heterogeneous hardware are increasingly used to meet the performance requirements of today's applications. These architectures are tedious to program because of their heterogeneity, as devices such as CPU, GPU, FPGA, and TPU provide different programming abstractions and may have disjoint memories, even if they are on the same machine. Moreover, applications are written by experts in the application domain rather than experts in parallel programming. Consequently, it is hard for programmers to: (1) write efficient code for each device, (2) distribute execution across devices, (3) orchestrate communication between devices, and (4) port code to new emerging devices. To address these problems, my goal is to design programming languages that provide a common domain-specific interface for all devices, and build compilers and runtime systems that generate efficient architecture-specific code for each device, distribute computation among devices, and move data between them efficiently.

The datasets and models used by AI applications are growing in size. With this growth, there is an increasing need to exploit sparsity in the dataset or the model for efficiency. For example, most of the weights (model) learned in many typical *deep neural networks* (DNN) may be pruned for faster inference without loss in accuracy. On the other hand, privacy of the datasets used must be preserved in many applications, especially if they run on public clouds. For example, applications may need to run DNN inference on medical or financial data without violating the data owner's privacy. Fully-Homomorphic Encryption (FHE) enables computation on encrypted data without requiring the secret key. In my view, an FHE scheme is akin to yet another heterogeneous device, so compilers can generate code for them to enforce privacy.

My dissertation research focuses on **distributed and heterogeneous graph analytics** and **privacy-preserving neural network inferencing**, and introduces new techniques in systems for sparse computing and privacy-preserving applications respectively. I designed and built a graph analytics system [10, 11] that partitions graphs [23] and optimizes communication on distributed, heterogeneous architectures, while providing application-specific fault-tolerance [12]. This system was an order of magnitude faster than existing systems at scale. I designed a new language [13] for FHE and built an optimizing compiler [16] that translates DNN inference to run on encrypted data using FHE efficiently, while guaranteeing security and accuracy. The generated codes were an order of magnitude faster than expert-written codes.

During my time at the graph AI startup, Katana Graph, I interacted with customers to understand their challenges in using AI systems. To address their major concerns, I led the graph engine team to build a distributed cloud platform for computing AI, analytics, and queries efficiently on large-scale graphs. My team built an in-memory and on-storage log-structured representation for labelled property graphs that is compact for sparse node and edge properties, while being efficient for both reading and updating the graph topology and properties. I designed and built the distributed graph querying engine that minimizes latency of business intelligence queries and scales well on distributed hosts. Katana Graph was significantly faster than our competition in the end-to-end time for a typical graph AI pipeline.

Overall, I have collaborated with researchers in different areas, including programming languages, systems, cryptography, security, and theory, and worked across the software stack such as algorithms, compilers, and low-level runtimes. The common theme in my research is to find important application domains, design programming abstractions for each application domain, and exploit domain knowledge at the right layer of the software stack to determine the right trade-off between productivity, portability, performance, and privacy. My vision is to build easy-to-use AI systems that enables application developers to reason about this trade-off.

Research Contributions

Distributed and Heterogeneous Graph Processing: Graph analytics systems provide a simple programming model to develop applications that analyze graphs like ranking web pages in search engines, finding clusters in biological networks, evaluating recommender systems, and finding shortest routes in maps. Such systems must handle large graphs like the Facebook friends graph, which has more than 2 billion nodes and 400 billion edges. Shared-memory systems like Galois [29], Ligra [34], and IrGL [30] are efficient but have limited memory and compute resources. Prior distributed-memory systems either did not scale or were not competitive with shared-memory systems. Moreover, they were restricted to CPUs and there was no way to reuse their techniques to leverage accelerators like GPUs. My dissertation addressed these issues.

Programming Model and Runtime: In my PLDI 2018 paper [10] and PACT 2019 paper [11] (one of the four Best Paper Nominees), I introduced a novel approach to build distributed graph analytics systems that exploits heterogeneity in processor types and partitioning policies. Programmers write applications in Galois for CPU or IrGL for GPU, and interface with **Gluon**, a communication-optimizing substrate. Gluon partitions the graph and offloads each partition to a CPU or GPU. I designed a new asynchronous execution model called **Bulk-Asynchronous Parallel (BASP)**. Exploiting the domain knowledge that graph analytics applications are resilient to stale reads, I introduced a novel way to synchronize the partitions *eventually*. I also created **communication optimizations** that exploit structural and temporal invariants of graph partitioning policies. Existing graph analytics (or sparse matrix) systems for a single CPU or GPU can use Gluon to scale out to distributed clusters with little effort.

Gluon’s modularity and abstraction does not come at the cost of performance. Execution time of Gluon improved by $\sim 3\times$ on average due to its communication optimizations, enabling it to scale well up to 256 CPUs and 64 GPUs. Gluon was faster than the prior state-of-the-art distributed CPU-only system, Gemini [36], by $\sim 4\times$ and $\sim 5\times$ on average using CPUs and GPUs respectively. It was on average $\sim 12\times$ faster than the only other distributed GPU-only system, Lux [28], at scale. Gluon is the only asynchronous distributed GPU graph system currently.

Resilience: My ASPLOS 2019 paper [12] tackles *fail-stop* faults (or machine crashes). The traditional way to tolerate faults is to *checkpoint* the application’s state periodically and *roll-back* the state to the last checkpoint when a fault occurs. Faults are rare, but checkpointing has overheads, even when no faults occur. My insight was that to recover from faults, it is sufficient to restart the computation (or *roll-forward*) from a state that will ultimately produce the correct result. Such states are called *valid* states. I classified graph algorithms and designed class-specific recovery protocols called **Phoenix** to compute a valid state from the current state. The computation function can be provided by programmers with little effort. Phoenix was incorporated into Gluon to make it **resilient to fail-stop faults**. Phoenix not only has no overhead in the absence of faults, but also outperforms checkpointing when few faults occur.

Software Stack: My work on Gluon has led to research on different aspects of graph processing. I collaborated with researchers to: (1) build a distributed training framework [21], on top of Gluon, for a class of applications like Word2Vec that use Skip-gram-like models to generate embeddings; (2) optimize the graph analytics runtime for byte-addressable memory [19]; (3) build the **Abelian** compiler [18] that compiles code written in its domain-specific language to run on distributed and heterogeneous clusters by generating CUDA code as well as the required communication code using Gluon; (4) develop an alternative to the Message Passing Interface (MPI) for graph analytics called **Lightweight Communication Interface (LCI)** [9]; (5) study the impact of different partitioning policies on execution time [20, 27] and build a fast **Customizable, Streaming Partitioner (CuSP)** [23]; and (6) develop distributed imple-

mentations of efficient algorithms for betweenness centrality [25], triangle counting [24], and belief propagation [35]; and (7) build programming frameworks [4, 3] for graph pattern mining (GPM) problems such as motif counting. During this time, I mentored graduate students and post-doctoral scholars, namely Loc Hoang, Bozhi You, Hochan Lee, Vishwesh Jatala, and Xuhao Chen. These works were published in VLDB, IPDPS, PPOPP, ICS, and Euro-Par.

Privacy-Preserving Deep Neural Network (DNN) Inference: Fully-Homomorphic Encryption (FHE) enables offloading both storage and computation of sensitive data to public clouds, without trusting software vendors, hardware vendors, or any third party with their secret key. However, developing FHE applications requires cryptographic expertise. In my PLDI 2019 paper [16], I built an end-to-end software stack called **CHET** for compiling tensor programs like DNN inference to run on FHE libraries [33, 26] that support *fixed-point* arithmetic. In my PLDI 2020 paper [13], I designed a new encrypted vector arithmetic language and compiler called **EVA** for developing general-purpose FHE applications.

Runtime: FHE schemes allow batching thousands of *plaintext* elements into a *ciphertext* vector and perform element-wise vector operations to amortize the cost. Like Intel MKL libraries, which have different implementations of linear algebra operations, I built a **library of homomorphic tensor operations** with different ways to map or *layout* tensors onto vectors.

Compiler: Encryption parameters influence the FHE computation. Setting these parameters low can make the computation insecure, whereas setting them large can increase the cost of homomorphic operations. Moreover, when these parameters are not sufficiently large, the encrypted result becomes corrupted. For two state-of-the-art FHE schemes [6, 5], I introduced compiler analysis to determine the minimum required encryption parameters for a program that ensures it is correct and secure. I then created compiler analysis to estimate the cost of a program using a cost model for the two schemes. CHET explores different layouts, **determines encryption parameters** and cost for each layout, and picks the best-performing one.

EVA is designed to be an intermediate representation that is a backend for other domain-specific compilers. I modified CHET to generate EVA programs for DNN inference. I built an optimizing compiler for EVA that generates correct and secure programs, while hiding all the complexities of the target FHE scheme. The compiler eliminates all common runtime exceptions and optimally inserts FHE instructions like rescaling and modulus switching.

CHET was the first compiler for DNN inference using FHE. It enabled homomorphic inference of deeper DNNs than was viable by experts' programming. It also allowed using FHE schemes that are much harder to program. Due to this and other optimizations, CHET was an order of magnitude faster than expert-written codes, even for small DNNs. CHET, when re-targeted onto EVA, is *only* 2-3 orders of magnitude slower than simple, unencrypted inference — a new landmark for FHE. EVA also enabled a wider adoption of FHE for other applications.

Research Agenda

Programming systems are essential to enable developers to extract good performance from heterogeneous architectures. However, programming support for exploiting sparsity on heterogeneous devices is inadequate. In my view, Fully-Homomorphic Encryption (FHE) libraries are akin to specialized heterogeneous architectures — except that they are specialized for privacy instead of performance or energy. Nevertheless, unlike other heterogeneous devices, FHE lacks programming support, even on dense, structured data. Consequently, instead of exploiting sparsity and enforcing privacy simultaneously, I am excited to continue working on programming systems for sparse computation and privacy-preserving computation independently.

Large-Scale Sparse Computation: Large unstructured datasets or graphs are ubiquitous [32]. Graphs are processed and analyzed by applications in many domains, such as:

Machine Learning: Graphs are fundamental to sparse machine learning. *Sparse DNNs* prune most of their weights during or after training without loss in accuracy (inference is performed on a sparse network). *Graph embeddings* learn embeddings for vertices in attributed graphs. *Word embeddings* like Word2Vec learn embeddings for unique words in a text corpus.

Databases: *Graph databases* support querying graphs with arbitrary attributes on nodes and edges using languages like Cypher. *Graph mining* discovers interesting patterns in a given graph (for example, *motif counting* counts the frequency of certain structural patterns).

I believe sparse machine learning and graph databases are the future of machine learning and databases respectively. My goal is to build programming systems that enable running them efficiently on a variety of architectures. To do this, I will leverage techniques that I developed in Gluon. For example, my recent work [?] builds on top of Gluon to scale out Word2Vec on distributed clusters. I plan to solve additional challenges posed by these applications, such as:

Morphing Datasets: In analytics, the graph does not change during computation. The graph structure may be updated during computation in graph databases, sparse deep learning, and graph embeddings. In some applications, the graph may be streamed; that is, nodes and edges may be added but not deleted. In general, nodes and edges may be added or deleted.

Availability of Datasets: In most graph analytics applications, computation on a node only accesses the incident edges or neighboring nodes. Graph partitioning [23] can thus statically make these available. This does not hold in other domains like graph mining. Graph databases and some graph analytics algorithms may also need availability of non-neighbor nodes or edges.

Hierarchical Parallelism: Graph analytics applications typically desire minimizing the latency of a query. Graph databases may instead desire maximizing the throughput of concurrent queries. Such applications expose parallelism both across and within queries.

Privacy-Preserving Computation: Among many privacy-preserving techniques, Fully-Homomorphic Encryption (FHE) offers unique features such as immunity to side-channel attacks and post-quantum safety. Cryptographic innovations have led to many FHE schemes. Similar to different hardware, different FHE schemes may provide different instruction sets: only bitwise arithmetic [7], only integer arithmetic [17, 2], or only fixed-point arithmetic [6, 5]. They have different performance and accuracy trade-offs to yield the same security [1].

The need to build compilers for developing privacy-preserving applications is well known [8, 22]. I believe compilers can not only make programming FHE easier but also make FHE programs faster. CHET is a first step in this direction for deep neural network (DNN) inference. There are many other applications that can benefit from FHE like machine learning, data analytics, and databases. Making it easy to develop them has several open problems.

Different applications may prefer (for efficiency or accuracy) different FHE schemes. Only a cryptographic expert who is intricately familiar with an FHE scheme can develop programs using it. Bitwise FHE schemes support arbitrary operations, whereas integer and fixed-point FHE schemes only support addition and multiplication but provide much better performance. Consequently, for fixed-point schemes, programmers approximate operations like rectified linear units (ReLU) in DNNs using polynomial activations. Moreover, fixed-point schemes perform approximate computation for efficiency. Future FHE schemes may have different characteristics.

My aim is to design **general-purpose programming languages** for FHE schemes that hide the cryptographic details of the schemes, and build compilers to translate programs in

those languages to run on the corresponding FHE schemes. This includes adding **approximation semantics** to the languages and approximation techniques to the compiler. For each application domain, I intend to build **domain-specific compilers** that choose the appropriate FHE scheme and target the corresponding general-purpose language. Leveraging my experience with polyhedral compiler techniques [15, 14, 31], I plan to generate efficient homomorphic kernels for high-level operations (like convolution). I envision building **distributed systems** for querying encrypted databases or analyzing encrypted big data on untrusted clouds.

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