

Accelerating Structural Sum Types

Luuk de Graaf

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1 Introduction

Abstractions in programming languages simplify code and allow for implicit exploitation of arising properties. Pure functional array languages utilize the independence between computations to implicitly parallelize array operations. This is complicated in languages that are not inherently thread-safe. Many high-performance applications adopt a data-oriented design, which centres around data transformations and avoiding abstractions around data. Both parallelization opportunities and cache efficiency are focal points of the data-oriented design paradigm.

A challenge with data-oriented design is representing non-uniform data efficiently while preserving vectorization opportunities and type safety. Operating on multiple variants of a type can be done on the type-level or on the value-level. In the context of iterating on a collection of variants, branching on a value tag or dynamically dispatching will inherently break vectorization. This means static polymorphism is a common way to operate on non-uniform data in data-parallel applications. In some cases this is impossible as the identity of a variant will only be known at runtime, such as exception states but also diverging states. Conceptually both approaches serve the same purpose, granting the ability to operate on multiple variants of a type. Unification of these concepts reformulates operating on non-uniform data to an optimization problem.

A type-safe way to achieve this is by elevating the concept of a mutual exclusive datatype to the type-level. This can be achieved through type-level constructors and datatype-generic functions. Such implementation can exist without it being natively supported as construct in the implementation language. This can be utilized by libraries, frameworks and embedded domain-specific languages that exist in languages that facilitate type-level programming, like Haskell.

1.1 Related Work

The contribution can be categorized as an interdisciplinary between three distinct fields. Initial objective was establishing computationally efficient representations for non-uniform data in data-parallel applications. This induced the need for a flexible and type-safe interface, which has been achieved through type-level and datatype generic programming. Relevance is established through an implementation in a data-parallel language embedded within Haskell.

Representation The memory representation of a datatype is often based on the functionality they perform within a language. In data-parallel applications primitive types are distributed over multiple arrays to facilitate vectorization. It is not apparent what the representation of a tagged union should be, as they inherently break vectorization in most cases. The functional data-parallel languages Accelerate[33] and Futhark[30] implicitly distribute primitive types in composite datatypes over multiple arrays. Both implementations have limited deduplication capabilities, but research has been done to integrate a memory efficient tagged union in Accelerate[33]. Game-engines, which deal with many clusters of data, have a fundamentally different approach as they have widely adopted the Entity-Component-System (ECS) pattern. Many implementations incite a collective re-organization of the internal representation when a variant change occurs at runtime. A type-safe and performant implementation is notably hard due to having to statically resolve all interactions between the representations, which means meta-programming and untyped code are extremely prevalent.

Type Interface Functional languages handle tagged unions safely through Algebraic Data Types (ADTs), where sum types categorize ADTs with multiple variants. Constructors can be local to an unique ADT (nominally typed) or exist as independent types (structurally typed). Deconstructing is done by pattern matching, where functions natively branch on the current active variant. In Haskell sum types are nominally typed, which means variants are not standalone types and cannot exist safely outside the ADT. Structural sum types are often called extensible or open sum types, as they do not have to be explicitly declared before use. In OCaml these are natively supported as polymorphic variants, while Haskell libraries such as *fastsum* or *extensible* implement them through the type system. An efficient internal representation can be derived statically through associated types[7]. Datatype generic functions, which depend on the structure of a datatype, can be used to create isomorphic mappings between representations. Both concepts are used in highly generic libraries for a wide-range of applications[28].

Implementation Libraries and domain-specific languages that are embedded construct their user-defined-types through the host-language. A shallow embedding operates directly on types native to the host-language, while deep embeddings construct an abstract syntax tree that is later evaluated. The latter offers flexibility on how user-defined types are implemented, as types exist both on the surface level and as construct within the abstract syntax tree. There are several approaches, which have been subject to research in the domain of circuit design.

- CλaSH is not deeply embedded and operates on user-defined types through generics[3].
- Hydra has the deep embedding constructs nested into the shallow embedding constructs[27].
- Kansas Lava has both embeddings exist in parallel under an encasing type[14].
- ForSyDe has both embeddings exist as standalone types[29].

An observation is that user extendability is limited on deeply embedded constructs as execution models must be updated. A proposed approach is to have a small deeply embedded core language that only supports constructs that are relevant for combinatorial optimizations[32]. The shallow embedding can be used to create an extensible and user-friendly interface to this core language. In the context of data-parallel applications and non-uniform data this leans itself to an implementation in the host-language.

2 Performance

There are many components that can influence the performance of a program. This grows the importance of being able to identify *bottlenecks* but also understanding the underlying technological performance considerations[16]. Within the first section fundamental optimizations related to the interaction between data and hardware are introduced. This is used to identify architecture agnostic performance considerations for array operations in the second section.

2.1 Optimizations

In the early days of computing, memory was seen as a way to store data indefinitely. As computational power of processors increased, the importance of main memory increased. Main memory is dependant on the advancements of random-access-memory (RAM), which stagnated due to both cost and physical limitations[9]. This put pressure on the software side to adapt to hardware components for optimizations, rather than merely the computational complexity of algorithms.

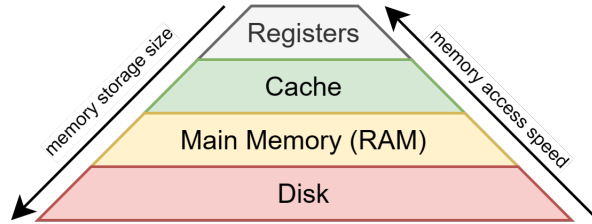


Figure 1: memory hierarchy

One of these hardware optimizations is cache storage, which accelerates memory accesses of predetermined data. The data is decided based on a cache replacement policy, often based on a temporal property. The cache operates independently of the operating system[9], and no direct control can be exercised.

Instructions Interfacing with processors is done through computer instructions. Fetching of an instruction is a memory operation, as it retrieves the instruction at the target of the program counter. Instructions operate on registers, which have distinct sizes depending on the architecture and their respective function. There are many instruction set architectures (ISA) and devices that implement distinct instruction sets. An intermediate representation (IR), such as the LLVM IR[19], can be used to create a uniform interface between these instruction sets[8]. Explicit use of these architecture exclusive instructions can be achieved through compiler intrinsics. Hardware design sometimes allows for executing specialized instructions¹, which are faster than their semantically equivalent instruction(s). This includes sacrificing accuracy for performance (floating-point), combining a sequence of instructions (arithmetic) or by parallel execution on multiple data elements (SIMD). SIMD instructions in particular are often very performant, as several steps within the execution pipeline can be parallelized. This process of instruction parallelization is called *vectorization*.

¹Note that the term *complex instruction* is avoided, as this concerns a compact *representation* of several instructions.

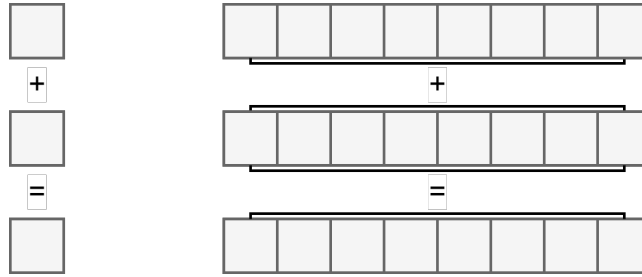


Figure 2: vectorization of a scalar addition operation

Register Pressure Registers can be considered the fastest available memory, as the data is ready to be used by an instruction. Within the context of registers this data is commonly referred to as a variable. Variables existing within registers before execution is a prerequisite for reasonable performance. This scheduling problem is to be considered a NP-complete problem[6]. Programming languages with any form of abstraction delegate this process to the compiler. This simplifies a lot of complexity, as only which data is being used by what instruction is relevant. In some cases there are too many live variables for the available registers, which *spills* the variable. This requires a variable to be stored outside registers, in a slower form of memory, and incites a delay upon use. This can be prevented by reducing the live-time of variables, reordering instructions and diversifying execution units.

Memory Access Time Semantically random-access-memory (RAM) implies that memory operations take around the same amount of time. In practice this does not hold for several reasons.

SRAM/DRAM On a modern system there often exist several different types of RAM, mostly driven by cost differences. The main forms of RAM are static RAM (SRAM) and dynamic RAM (DRAM). SRAM uses six transistors to represent a single bit, while DRAM only uses one transistor with a single capacitor. A capacitor loses electrons over time which means data has to be refreshed repeatedly to preserve its data. A refresh requires both read and write operations, which interferes with other memory operations. This makes DRAM inconsistent and on average significantly slower but much cheaper to produce due to requiring less transistors.[9]

Propagation Data is transferred by using electrical charges through semi-conductors. This creates a physical limitation dictated by physical distance and temperature. This is called propagation delay and a hard limitation to the rate at which components can operate on. SRAM is often located physically closer to the execution units to utilize the faster memory access more effectively.

DMA A processing unit needs to forward the requested data to the targeted location, which takes up processing time. Direct-memory-access (DMA) is an interface for hardware components and allows memory operations to be more organized. This allows for large scale memory operations to be performed efficiently and independently of the main processor. It requires use of several buses which means some processors must idle at seemingly random periods of time. This means that other hardware components can influence the memory access time.

Caching Due to hardware related discrepancies in memory access time, it can be beneficial to organize data according to the memory access time. One way to achieve this is by caching data, that is storing a *copy* of the data in faster accessible medium. A cache is generally made of SRAM and resides close to the processor, which allows memory accesses to be magnitudes faster than the equivalent main memory access[9]. When data already exist in the cache it is referred to as a *cache hit*, otherwise a *cache miss*. Deciding which data is cached and for how long is a cache replacement policy. Adapting to these policies simplifies the scheduling and minimizes the amount of cache misses.

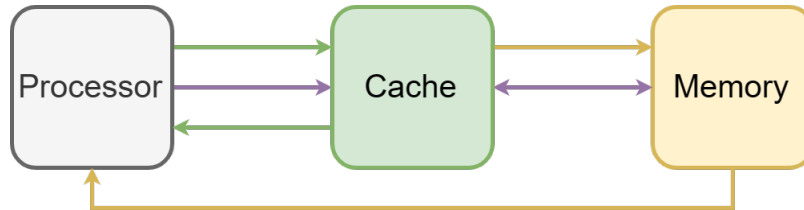


Figure 3: cache hit (green), cache miss (yellow) and replacement (purple)

Caching of data can be done after the data has been retrieved, which means the delay already has occurred. This can be avoided by requesting data in advance and storing it a cache prematurely, so called cache prefetching. This is done by analyzing future instructions (hardware) and instructions that *hint* at the future use of data (software)[4].

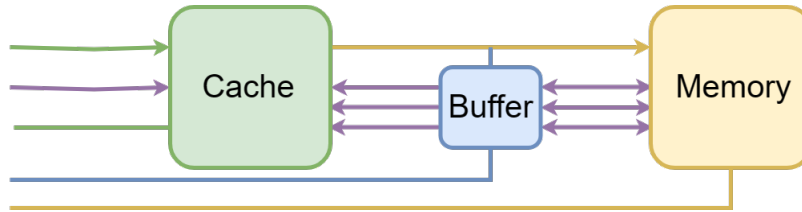


Figure 4: prefetch based on information (blue) from cache miss and processor instructions

This is harder when a branch is encountered, as both the data and the next instructions are uncertain. Speculatively executing these uncertain instructions can be performant if the overhead of redundant work remains small enough. Rather than executing unconditionally, some processors execute the most likely to happen branch based on some parameters (branch prediction)[31].

Parallelism Instruction-level parallelism is the parallel execution of multiple instructions[31]. This can be done by dividing instructions into several steps and outsourcing each step to a distinct processor unit (instruction pipelining). Shuffling the order of instructions can allow more processor units to work in parallel (out-of-order execution). Duplicate units and independent instructions allows for additional parallelism (superscalar execution).

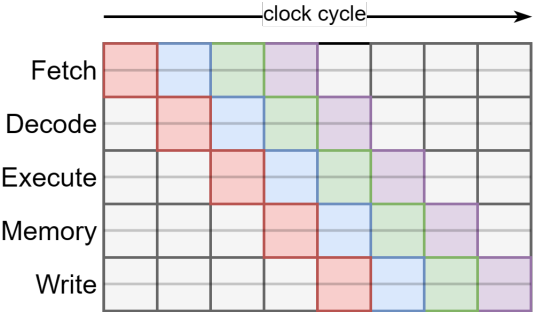


Figure 5: instruction pipelining: each color represents an instruction

Data-level parallelism executes an instruction on several data elements, such as the previously discussed SIMD instructions. Specialized processors sometimes either fully pipeline the data (vector processing) or allow for some form of autonomy (multithreading). Both share instruction fetching and decoding, but threads have their own program counter which allows for an independent sequence of instructions.

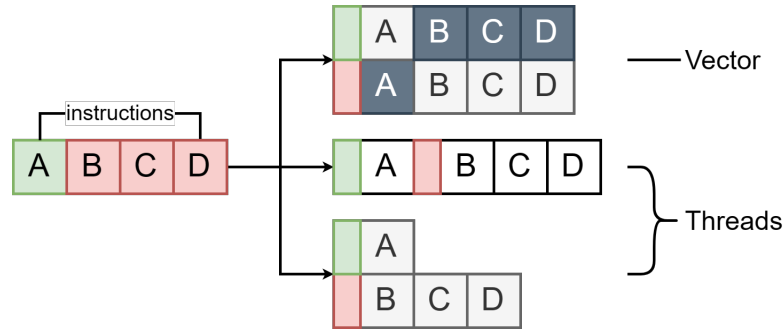


Figure 6: branch instructions: masking (vector) vs independent sequence (threads)

Execution of threads can be done concurrently, which can be useful to hide latencies (context-switching). In parallel is also possible with multi-core processors, which have several processors units (cores) that can support multiple threads. Cores are often not independent processors and might share several components with other cores, such as caches[20].

2.2 Principles

There are many components that can influence the performance of a program, some of which were discussed in previous sections. This makes general statements on optimizations often weak, as the interaction between these components is complex. Focusing on a particular area, such as iterating on data elements, allows for stronger arguments. Within this section previously discussed optimizations will be discussed in the context of iterating on many elements.

Contiguous A rudimentary reason for contiguously allocated data is that it creates structure, which can be used to organize data. Arrays utilize their structure to align elements, such that each element can be identified in constant time² through a linear function. This is also used for compound datatypes, where structure and the type can identify the memory location of each field. The structure also simplifies work distribution between threads, as it is a matter of constant offsets. For vectorization contiguous data is a prerequisite as instructions operate on singular contiguous blocks of data. If data is not spatial adjacent in memory, data must aligned temporarily or complex interleaving methods must be used[25]. In the general case compound datatypes interfere with vectorization, as spatial adjacent data is not of the same type. Parallel arrays solve this by creating a distinct array for each primitive type (Struct of Array) so that each field can be vectorized.

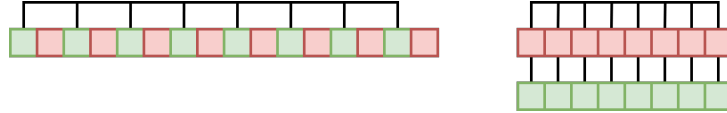


Figure 7: compound datatype array (1) and a parallel array (2)

Caches also operate with contiguous blocks of memory, which means spatial adjacent data within a fixed alignment are stored together. This lends itself well to contiguous allocated data, as it means the least amount of cache blocks are required irrespective of block size and alignment. In addition all memory accesses use the same linear function, a *constant stride* access behavior, which makes it receptive to hardware cache prefetching[4].

Access Patterns As the cache is finite a cache block can be ejected prematurely. This exists for data within the same block but also when the same block is required at multiple times. Increasing temporal locality is done by avoiding random accesses and organizing computations order around data usage. This is non-trivial in iterations where multiple indices are accessed (stencils) or computations that inherently involve random access.

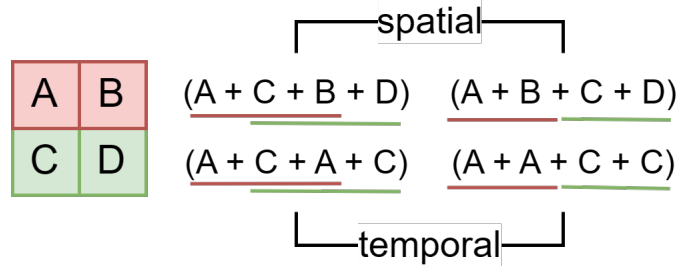


Figure 8: exploitation of spatial and temporal locality

²Both in *time complexity* and within *computer architecture* norms, as data access is a single instruction, unlike pointer trees and hash tables.

One way to apply this to iterating on many elements, is to iterate one subset of elements at a time (tiling). This can be further improved by also accounting for shared resources, by grouping elements that use the same resource in their instruction sequence. This is explored in raytracing[1], where spatial locality of rays is used to exploit the cache coherence within the traversal of a tree. These techniques are also important for multi-core processors, as it reduces the need for data to exist in multiple caches.

Branching Pipelining instructions is not possible when the sequence of instructions is dependant on the result of a previous instruction. This limits instruction-level parallelism, which is solved through various unconditional instruction executions[31]. Either by discarding the computed results or by *flushing* the pipeline when the wrong branch is predicted, both of which intuitively have an overhead. A compiler can eliminate³ branches or move loop-invariant code to facilitate instruction-level parallelism[12]. These optimizations are not absolute, as an increase in instructions can pressure registers and the cache. It is also limited to instructions that cannot fail or overflow, as both can introduce unintentional side-effects.

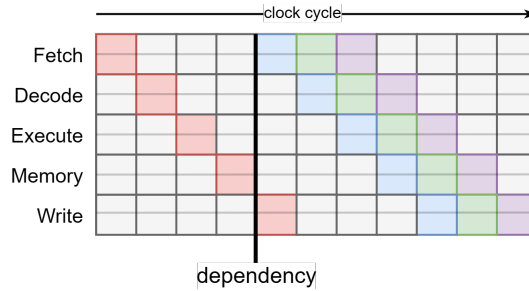


Figure 9: branch introduces dependency on execution of instruction (red)

Branching is also problematic for vectorization, as all data within a certain alignment must follow the same sequence of instructions. This can be resolved through the use of a *bitmask*, which can nullify parts of a result[12]. The additional instructions and computing bit masks can prevent performance from vectorization in certain situations. A notable application is sequential loops, where unrolling creates an opportunity to vectorize the scalar instructions. Automatic vectorization is an active field of research, and limitations have been primarily attributed to the lack of analysis information available to compilers[10]. This means branchless code and simplifying control flow allows the compiler to vectorize in more instances.

Specialized processors where an instruction sequence is distributed over many cores are limited to executing all branches. This is minimized through the use of Streaming Multiprocessors (SM), which contains several cores and fetch their own instructions. Streaming Multiprocessors operate and schedule warps, which often contain 32 threads. When divergence between these threads occurs (*branch divergence*) the instructions will in the general case be executed in lockstep[26].

³Either by proving the branch will never be executed or by replacing the branch with a *conditional move* instruction, which only writes the result on true.

2.3 Data structures

A fundamental aspect of computing is data structures, which is a constant overhead for all computations. For collective operations arrays are essential; as they have a constant access time, are contiguously allocated and access can be parallelized. Composite datatypes within arrays introduce some considerations. One is the *implicit* use of parallel arrays, where each primitive datatype is stored in a distinct array. This enables vectorization opportunities, but a random access pattern might cause additional cache blocks to be cycled between. Since collective operations control the access pattern, parallel arrays are often a natural choice for array languages. The consideration for both structurally and functionally distinct data, now referred to as variant, is often complex. Variants can be represented on an individual basis (element-wise) or collectively (variant-wise). Usage and implementations of these approaches are explored in this chapter. Within this chapter the assumption is made that parallel arrays are used, as they align with the intention to vectorize operations. The example composite datatype has type **A**, and either has type **B** or type **C**.

2.3.1 Element-wise

For each element the choice of variant is represented, which introduces branching and in the general case will break vectorization. As variants are not grouped, functions cannot iterate on a specific variant without iterating on the complete array. The main advantage is that a variant change can be done independent of other elements, and thus can be parallelized. A practical consideration is that each element in an array must be structurally the same, that is they occupy the same memory space. This is a limitation which enforces that each index can determine the location of an element. For parallel arrays this restriction applies for all arrays individually[33].

Tagged Union Multiple variants can be represented through a tag and a fixed size data component with multiple representations, so called *union*. The tag is used to identify the current representation of the union. A naive implementation creates an array for each field of each variant, which means the memory usage is cumulative for each variant. A compact tagged union overlaps fields of variants, as only one representation can be valid at a time. This can in theory reduce the size to the largest variant and the accompanied tag, but this is complicated due to alignment requirements[33].

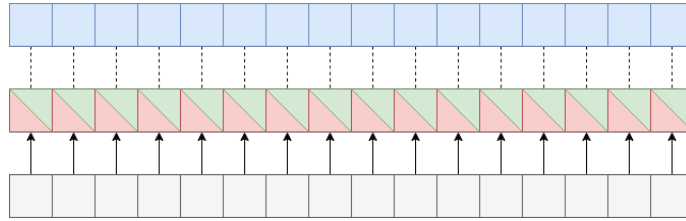


Figure 10: index implicit and tag (gray) identify the data representation

Tagged Pointer Another way to comply with elements being structurally the same is to use a form of indirection, in this case a pointer to memory. The indirection allows variants to escape the uniform size restriction, but there are several notable complications. General complications around pointers, such as being unsafe to operate on and complicating garbage collection apply. In addition, pointers that point to the same data (alias) can prevent parallelization due to possible race conditions. These can be partly solved through language constructs; such as smart pointers, immutable data or abstracting the use of pointers altogether.

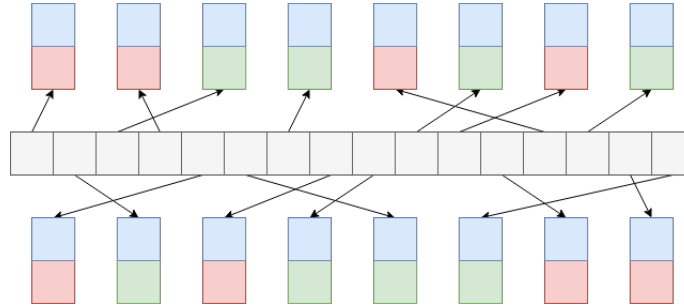
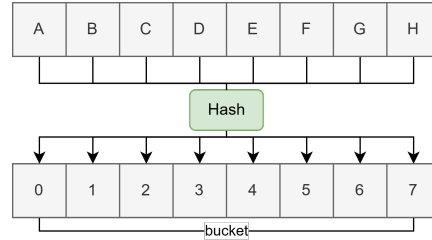


Figure 11: tag and pointer (gray) identify the location and representation.

The key issue is that a change in variant requires new data to be allocated and the pointer to be adjusted. This allocation means there is no guarantee that the data is contiguous, which in addition to the required branching prevents any vectorization efforts. The indirection and fragmented memory is also problematic for cache efficiency, as it is unpredictable and a cache block is not used effectively.

Entity A notable observation is that the re-allocation of a variant change causes the data to be not contiguous, not the indirection in itself. This can be illustrated through a hash table data structure, where a key is mapped to a value within an array (bucket). Any collective operation on the hash table can be vectorized by disregarding the hashing and using the internal array directly, as computations are inherently independent and order is irrelevant.



Entities within the ECS pattern function similarly, a form of indirection that is not used by the collective operations. Represented as a single heterogeneous array, which internally consists of several variant-wise collections. It will mean that variant choice is not *directly* represented on an element basis, which has several implications.

Stable The same entity is not guaranteed to refer to the same data, the entity is no longer stable across structural changes. The reverse also holds, the data is not guaranteed to have the same entity along iterations. This can be solved by tracking the location of entities *or* annotating the data with their entity. These approaches can be complementary for performance reasons, but they are collectively isomorphic⁴ through gather and scatter operations.

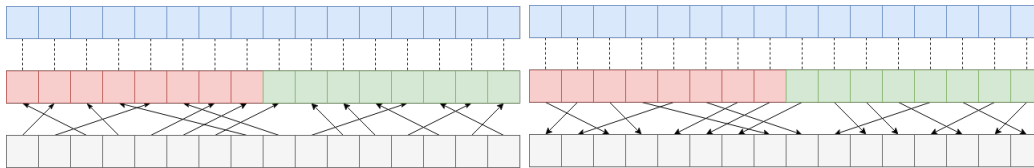


Figure 12: persistent array with indirection (1) or annotate the data with their index (2).

For many array operations stableness is excessive, as it means data is discriminated on the basis of their index. The implicit connection that data with the same index has can be represented through a (temporary) datatype.

Independent Elements can no longer change their variant independently of other elements, which can be problematic for parallelism. Depending on the way variants are grouped, there can also be a significant cost associated with regrouping variants. This can be minimized by delaying structural changes indefinitely, by using a tagged union approach. Regrouping variants is a performance consideration between the cost of regrouping and having to branch for future iterations.

⁴A single entity cannot identify the data in constant time, without an array of pointers. A data element cannot identify the entity in constant time, without the entity as data.

2.3.2 Variant-wise

Grouping variants means all data is uniform, contiguously allocated and there exist no inherit branching within the same grouping of variants. This can be achieved through an array for each variant, but also grouping *within* the same array and using segment descriptors. The latter is effectively an untagged union, where the representation is determined by the index within the array. Both allow instructions to be vectorized, but there exist several other considerations.

- grouping As stated in the previous section, regrouping variants to a variant-wise collection is a performance consideration. When variants are stored in separate arrays, the amount of a certain variant must be known before allocation. When this is dependant on a computation, it can be retrieved through an additional scan or atomically⁵ counting any structural change, which adds an overhead. This is not required for a singular array if the total remains the same.
- immutable An important consideration for purely functional languages is that values, and therefore arrays, are to be considered immutable. This means that *updating* parts of an array efficiently is non-trivial. It must be proven that the array before update will never be used again, otherwise both arrays must co-exist in memory. This is inefficient for small updates and grows the necessity to *destructively update*[18].
- automatic Most compilers support automatic vectorization of iterations with flexible bounds, where the final leftover iteration is not vectorized. This overhead can be a significant when the loop is extensively unrolled. This is minimized through epilogue vectorization, which (re-)applies loop vectorization to the remaining scalar code. In practice data must be aligned along specific byte boundaries to be vectorized, which is challenging for (dynamic) regions within an array and not always analyzed by compilers[10].
- operable An undiscussed benefit of parallel arrays is that fields can be operated on independent of other fields, as they are distinct arrays. This is also possible for *regions* within an array, but this is less trivial and often requires explicit support in array languages[11].

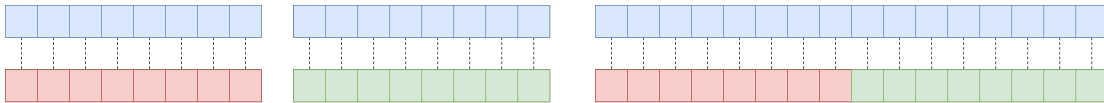


Figure 13: distinct arrays (1) or distributed in a single array (2)

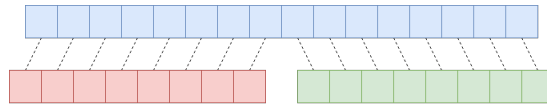


Figure 14: combination of both approaches

⁵Atomic instructions prevent interruptions by other processes and are thread-safe.

2.4 Memory Representation

Memory instructions operate on fixed boundaries, which means operations that overlap these boundaries require additional but strictly unnecessary instructions. A natural alignment of a datatype is achieved by aligning all types according to the instructions that access them⁶. Many compilers introduce *padding* to enforce natural alignment. While computationally efficient, the alternative of *packing* types together can be preferred for a smaller memory footprint. Both approaches can be used to ensure the datatypes align with cache lines.

Figure 15: data alignment example with cache lines (c++ code)

Parallel arrays (Struct of Arrays) have a natural alignment by default as they contain primitives types, which are naturally aligned. General purpose languages often default to the Array of Struct, while data-parallel applications use the Struct of Arrays representation. A zero-cost abstraction that can ergonomically switch between these constructs is non-trivial. An interface to index access with an intermediate structure can break automatic vectorization[17]. In addition the different internal representations must be statically definable and able to be handled by the data structures. Many C++ libraries utilize *class templates* to achieve this[17]. Being able to switch between representations was an initial focal point of the experimental language *Jai*, a c-like programming language for games. The switch between representations is currently possible through a more general pre-processors macro's approach.

⁶SIMD instructions

3 Interface

A preliminary conclusion of the previous chapter is that a performant internal representation cannot be deduced from a mere theoretical framework. With this in mind it is important for high performance oriented applications to be flexible within the internal representation of datatypes. This is important for both composite types and data structures. Within this chapter a modular interface is explored for iterating on collections of non-uniform data.

3.1 Data Structure

As discussed in the data structures section, there are two internal representations for collections of non-uniform data. Variants of a particular type are stored either element-wise or variant-wise. There are several considerations for a data structure that is agnostic to if it stores non-uniform data in element-wise or a variant-wise way. A variant-wise collection can operate on only the relevant variants, while an element-wise is forced to discover that at runtime. To avoid redundant iterations for variant-wise collections, a function must be able to be defined on a subset of all possible variants. This section will be used to explain how the ECS-pattern handles operating on some variants and extending the use case to Algebraic Data Types.

3.1.1 Entity-Component-System

The ECS pattern is arguably a reaction to the prevalence of object-oriented languages within game engines. The premise is to organize game-logic within functions rather than components, where the relation between components is flexible[21]. In contrast to inheritance, where relations are statically determined and game-logic is embedded within an predetermined hierarchy. The pattern is often combined with data-oriented design.

Entity An entity is idiomatically a set of components, but instantiated as a globally unique index that can identify the associated data components. An entity can generally only have one component. This means an entity is effectively a *set* of components.

Systems Systems operate on all entities that contain such a set of components, where components are *mutated*. Structural changes to entities are invoked through statements.

Systems are top-level functions that operate on all entities that contain a set of components. An entity is idiomatically a set of components, but instantiated as a globally unique index that can identify the associated data components. Rather than iterating with this index, systems utilize the implicit structure of an entity to directly iterate on the data components. The 'type' of an entity can be modified by removing or adding components.

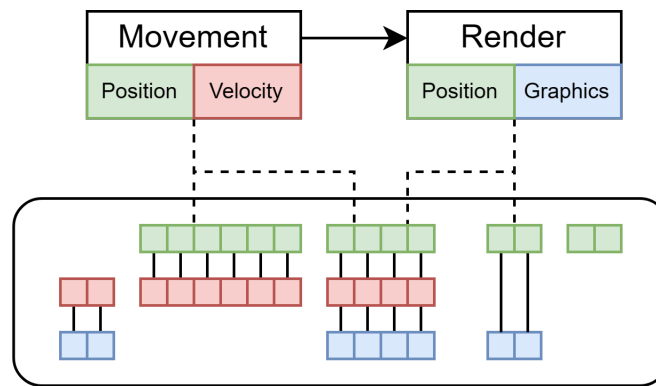


Figure 16: conceptual entity-component-system representation of systems

The ECS design pattern is arguably inherently imperative, due to prevalence of mutating state. Apecs, an ECS implementation in Haskell, achieves this imperative style through monads[5]. All these considerations are related to the interpretation of the relation between components, in essence the *type* of an entity. Rather than emulating ECS, existing type systems can be used to handle the relation between data.

Apecs[5] is an ECS library in Haskell, with experimental support for concurrency through the Software Transactional Memory (STM) monad[15]. The STM monad utilizes atomic instructions to achieve concurrency within a monadic context. Entities are stored with an integer dictionary, but can be explicitly stored in a sparse fixed size *cache* which allows for constant access time.

Specs is an ECS library in Rust[13], with native support for parallelism. It supports several storages such as: a tree data structure, dense vector, sparse vector and an hashmap. Iteration on entities is done by specifying the relation between the components: join, optional and excluded. An entity can be *flagged* (tag) to denote events such as the destruction of the entity.

Unity is a game-engine which released their production ready Data-Oriented-Tech-Stack (DOTS) in 2022, which centres around an ECS implementation which they have patented[2]. It uses LLVM to optimize and vectorize C# code (burst compiler) and has access to their internal c++ library for

parallel and concurrent tasks (job system). The ECS implementation heavily employs the .NET Compiler Platform Roslyn to generate source-code for iterations on user-defined datatypes. An `Entity` is idiomatically a composite datatype but implemented as an `identifier` with a `version`⁷. A single array keeps track of all entities, without data components. Each `Entity` and related data components are stored in a `Chunk`, a fixed size buffer of 16000 bytes, alongside other entities with the same `Archetype`⁸. Instead of pattern matching, a `Query` matches on certain properties of entities, such as containing a certain component. Collective operations, such as a `Job`, operate on a `Chunk` directly. Structural changes can be queued in parallel, but create a sync-point when executed and involves entities to be moved between chunks. This is not required for an `IEnableComponent`, which functions as an tagged component akin to the `Maybe a` type. A notable observation is that delaying structural changes has side-effects as queued structural changes are not taking in account.

⁷Destroying an entity increments the `version`, which means copies of entities know they are destroyed and the `identifier` can be reused at a later point.

⁸An `ISharedComponent` extends this to the value of a component, which means each value has a unique `Chunk` and the value can be stored within the `Chunk` header.

3.1.2 Algebraic Data Type

Functional languages handle tagged unions safely through algebraic data types (ADTs). A product type (\times) is the combination of datatypes, while a sum type ($+$) is the alternation between datatypes. It is often useful to discriminate between variations of a datatype, which is generally done through a data constructor.

```
data Maybe a = Just a | Nothing
```

Deconstructing an algebraic data type is done by pattern matching on a data constructor. The pattern match can exhaustively match on all variants, as the data constructors of variants are known at compile-time. It can be seen as a native control-flow mechanism that ensures only the operations on the active variant are applied.

```
fmap :: (a -> b) -> Maybe a -> Maybe b
fmap f (Just a) = Just (f a)
fmap f Nothing  = Nothing
```

In Haskell, algebraic data types are distinguishable by name (nominally typed) and therefore explicitly declared. This means data constructors are local to the declared type and pattern matching happens within the same type. The type signature of the `fmap` function provides no information on the potential structural change of a datatype. It is possible to return `Nothing` for both cases⁹. A function that takes `Just a` and returns `Just b` ensures that the *collective identity* is preserved in a collective operation, irrespective of the data transformation. This exact definition is not possible due to being nominally typed, as `Just a` is not a type but a data constructor under the type `Maybe a`. In some cases, such as a safe division function, the introduced branching is inherent to function and is now explicit in the type definition.

```
fmap :: (a -> b) -> Just a -> Just b
fmap f (Just a) = Just (f a)

divide :: Int -> Int -> (Just Int | Nothing)
divide _ 0 = Nothing
divide n m = Just (n `div` m)
```

In this case a function is defined on the structure of a type, the data constructor of algebraic data types. `Maybe a` is now an alias for the mutually exclusive relationship `Just a | Nothing`, rather than a unique and standalone type. This generalizes variance to be between all types. OCaml calls these *polymorphic variants*¹⁰, while other functional languages generally refer to them as *extensible* or *open sum types*. A motivating example is that a collection of `Maybe a` can be an heterogeneous collection or two variant-wise collections of `Just a` and `Nothing`¹¹. While the former involves branching for `fmap`, the latter can ignore the `Nothing` collection and vectorize the `fmap` function. This flexibility aligns with the intention to create a modular system that is agnostic to the internal representation.

⁹ `Just b` is not possible as it can only be inferred through `Just a` and the `a -> b` function.

¹⁰ OCaml also implements nominally typed sum types, so called *variants*.

¹¹ As `Nothing` does not hold data, a size descriptor is sufficient.

3.2 Type-level programming

deriving intermediate data structures

3.2.1 Kinds

A value is categorized by types, while a type is categorized by *kinds*. This is relevant when discussing type constructors, where each constructor with a different arity has a distinguishable kind. A well known exposition of type constructors are parametric polymorphic data types, which take type variables as argument. While a lot of languages support polymorphic data types, the concept of kinds is not evident as only concrete types are able to be used for arguments. Haskell supports higher-kinded types, which are analogous to higher-order functions for types, which makes kinds apparent.

```
2.5f      :: Float
Float      :: *
Option a   :: * -> *
Option Float :: *
Apply f x   :: (* -> *) -> * -> *
```

Type constructors can be used to encode data statically, such as Peano numbers. The parametric `Succ a` and `Nil` types are axioms that can be used to construct a natural number on the type-level. By default these exist in an open universe, which means ill-formed expressions can be created. On the type-level this can be resolved by Generalized Algebraic Data Types (GADTs), a Haskell extension. It allows the type variables of constructors to diverge from the more general type.

```
// open universe where 'a' can be anything
data Succ a
data Nil

// closed universe under the phantom type 'a'
data Natural a where
  Succ :: Natural b -> Natural (Natural b)
  Nil  :: Natural ()
```

The consequence is that deconstructing a GADT will refine the type. This can be used to construct evidence of certain properties by pattern matching on data constructors. An observation is that this is a categorization of types, similar to how the kind `*` represents all concrete types. The `DataKind` extension promotes types to the kind-level and constructors to the type-level. The kind `Natural` includes the types `Succ (a :: Natural)` and `Nil`. It both creates a closed universe and allows other type constructors to expect the more precise kind `Natural`. A limitation is that the construction of the type, which is needed for arithmetic operations, is guarded by the definition of `Natural`.

```
data Natural = Succ Natural | Nil | Add Natural Natural | Minus Natural Natural
```

On the value-level this is made easier by functions that transform their input into another output type. Translated to the type-level it means type-level functions that transform an input kind into an output kind.

3.2.2 Type Family

A way to approach type-level functions is to see it as a type dependent on the instantiation of a type variable. This is akin to functions in type classes, where type-indexing allows functions to be overloaded. Haskell reuses this functionality for types, categorizable as *associated types*[7]. This is particularly useful for domain-specific languages, as an instance can have a specialized return type. Accelerate uses the `Elt` class to map between surface types and an internal representation.

```
class (Elt a) where
  type EltR a :: *
  toElt      :: a -> EltR a
  fromElt    :: EltR a -> a
```

While these integrate well with type classes, type families is the terminology for the standalone concept. A `data family` has unique types associated with the type, while a `type family` is merely the type synonym equivalent. In some instances this is insufficient to represent a function, as the type checker is unsure which instance to use. A closed type family attempts the instances in order of definition, which expresses itself in being able to pattern match on types.

```
type family Elem a (bs :: [b]) :: Bool where
  Elem x '[]      = False      -- no
  Elem x (x : ys) = True       -- yes
  Elem x (y : ys) = Elem x ys  -- no, but recurse
```

An annoying limitation is that type families in Haskell cannot be partially applied, which means a lot of boilerplate is required to capture more complex functions. It cannot be partially applied due to partially applied type synonyms requiring full fledged higher-order unification, which is not supported in Haskell.

3.2.3 Type Structure

With closed type families it is possible to derive compact layouts for multiple variants of a type. As a memory layout only concerns itself with the bit sizes of types, the intermediate structure will be the previously discussed natural number. The `DataKinds` extension natively supports the `Nat` kind with arithmetic expressions and literals for syntax. While mapping of primitive types to their corresponding natural number is trivial, this is not the case for user-defined datatypes.

```
type family BitSize (a :: *) :: Nat where
  BitSize Word8    = 8
  BitSize Custom   = ?
```

It is not possible to statically derive the bit size of the `Custom` type within the type family. For this the types of which `Custom` is composed must be known to the type family. This means the structure of the type must be apparent to the type family. One way is to use a kind more specific than `*` that is explicit in the composition, such as the `Natural` kind but for all datatypes. Another way is to enforce an implicit constraint by ensuring the type can be constructed with a particular GADT. The latter is used by Accelerate where the `TupR` constructor ensures that the type is composed of only units, singles and pairs. The function `eltR` enforces this by requiring the associated type `EltR a` to have a mapping to the `TupR` type¹². The GADT approach is preferable when access to the structure on the value-level is needed, which is the case for future datatype generic programming endeavors.

```
class (Elt a) where
  type EltR a :: *
  eltR      :: TupR ScalarType (EltR a)

data TupR s a where
  TupRunit  ::                      TupR s ()
  TupRsingle :: s a                -> TupR s a
  TupRpair   :: TupR s a -> TupR s b -> TupR s (a, b)

type family BitSize (a :: *) :: Nat where
  BitSize (a, b)    = BitSize a + BitSize b
  BitSize ()        = 0
  BitSize Word8     = 8
```

¹²Note this can be circumvented by merely returning a bottom type such as `undefined`

3.2.4 Layout

For simplification the list *kind*, that is the promoted native list type, is used to denote all possible variants of a certain type.

An apparent structure also allows for type families to make informed decisions about an optimal layout.

In the case of Accelerate each primitive type within a tuple is spread out over multiple arrays.

3.3 Datatype generic programming

4 Implementation

5 Future work

6 Conclusion

7 Extra

Implementation Accelerate[33] and Futhark[30] are functional array languages that support

C/C++ An union is a structure identical to the largest member of the union. Accessing a member of the union extracts the raw value out of the union, independent of the last assigned variant. This makes using unions inherently not type-safe to use. The variant class template partly solves this by attaching a tag and throwing a runtime error when accessing a variant that was not assigned.

Haskell sum type / instances

Dynamic programming languages

Entity-Component-System Systems are top-level functions that operate on all entities that contain a set of components. An entity is idiomatically a set of components, but instantiated as a globally unique index that can identify the associated data components. Rather than iterating with this index, systems utilize the implicit structure of an entity to directly iterate on the data components. The 'type' of an entity can be modified by removing or adding components.

The ECS pattern is arguably a reaction to the prevalence of object-oriented languages within game engines. The premise is to organize game-logic within systems rather than components, where the relation between components is flexible[21]. In contrast to inheritance, where relations are statically determined and game-logic is embedded within an hierarchy. In this chapter the type interpretation of entities is discussed, and linked to functional languages.

An entity is fundamentally a composition of components, irrespective of which components can be combined. As many object-oriented languages are nominally typed, an entity is often implemented to only have one component of each. This means an entity is effectively a *set* of components. Systems operate on all entities that contain such a set of components, where components are *mutated*. Structural changes to entities are invoked through statements.

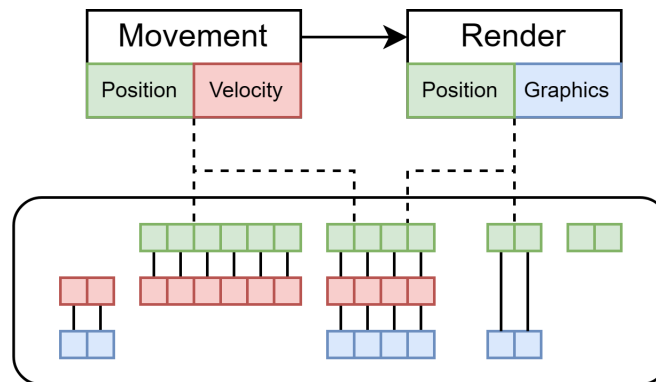


Figure 17: conceptual entity-component-system representation of systems

The ECS design pattern is arguably inherently imperative, due to prevalence of mutating state. *Apex*, an ECS implementation in Haskell, achieves this imperative style through monads[5]. All these considerations are related to the interpretation of the relation between components, in essence the *type* of an entity. Rather than emulating ECS, existing type systems can be used to handle the relation between data.

Apex[5] is an ECS library in Haskell, with experimental support for concurrency through the Software Transactional Memory (STM) monad[15]. The STM monad utilizes atomic instructions to achieve concurrency within a monadic context. Entities are stored with an integer dictionary, but can be explicitly stored in a sparse fixed size *cache* which allows for constant access time.

Specs is an ECS library in Rust[13], with native support for parallelism. It supports several storages such as: a tree data structure, dense vector, sparse vector and an hashmap. Iteration on entities is done by specifying the relation between the components: join, optional and excluded. An entity can be *flagged* (tag) to denote events such as the destruction of the entity.

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paragraphCode Generation

A common factor with data type representation is that they are understandably heavily ingrained within a compiler. This can make an ergonomic and zero-cost abstraction problematic as a compiler will treat the functionally identical types as distinct. This can be resolved by generating code dependent on the concrete instantiation of the type.

Algebraic Data Type

Accelerate Accelerate is a data-parallel array language deeply embedded within Haskell. An abstract syntax tree (AST) is created and optimized by Accelerate within Haskell’s runtime system. This greatly improves useability, as it can function as an Haskell library, at the cost of executing code within another runtime system. The garbage collection of the Haskell runtime system is speculated to hinder performance[34]. A type-safe interface to the compiler infrastructure LLVM enabled the creation of two backends: GPU and multi-core CPU’s[22]. These backends can be used to execute a small set of collective operators in parallel; such as **map**, **fold** and **stencil**.

```
dotp :: Acc (Vector Float) -> Acc (Vector Float) -> Acc (Scalar Float)
dotp xs ys = fold (+) 0 (zipWith (*) xs ys)
```

¹³Destroying an entity increments the **version**, which means copies of entities know they are destroyed and the **identifier** can be reused at a later point.

¹⁴An **ISharedComponent** extends this to the value of a component, which means each value has a unique **Chunk** and the value can be stored within the **Chunk** header.

The inherit thread-safety and fixed set of collective operators guarantee a consistent application of data-level parallelization. It in addition allows for these collective operators to be heavily optimized in isolation, but also in relation to other collective operators. A naive implementation of `dotp` would create an intermediate array for the results of the `zipWith` function[23]. Fusing these operations would eliminate an iteration and the intermediate array, at the cost of potential register pressure. Accelerate fuses these collective operations, unless the fusion introduces duplicate work or the `compute` function is explicitly called.

As Accelerate is embedded within Haskell, it uses algebraic data types and tuples for composite datatypes. Datatypes must be *lifted* into the abstract syntax tree of Accelerate, which is implemented for all native types. As algebraic data types are not native, pattern synonyms are used to create an isomorphic mapping *at compile-time* between the Haskell and the Accelerate datatype. As pattern matching cannot be overloaded in Haskell, the `match` operator is used to inject the required branching[24].

```
mkPattern ''Maybe

apply :: (a -> b) -> Maybe a -> Maybe b
apply f = match (fmap f)

fmap :: (a -> b) -> Maybe a -> Maybe b
fmap f (Just_ a) = Just_ (f a)
fmap f Nothing_ = Nothing_
```

Currently Accelerate uses a non-compact tagged union representation for sum types. Research has been done on a compact tagged union representation for parallel arrays, which has been named a *Recursive Tagged Union*[33]. The representation uses a unified tag for nested sum types, which optimizes memory usage at the cost of tag (de-)construction. It has been partly implemented in Accelerate, and has not yet been benchmarked.

An *embedded* language defines its terms and values in a *host language*. There are various degrees of embedding... shallow, deep, combinator, meta, compiler. A problem is embedded pattern matching... as choice elements are evaluated in the host.

CLaSH A domain-specific language for circuit design that is embedded within Haskell. Choice elements, such as algebraic data types, only exist as functions outside the syntactic elements of the language. User-defined types are thus restricted to product types and enumeration types, i.e. a sum type without any fields. [3]

Lava Another domain-specific language for circuit design that is embedded within Haskell.

<https://www.haskell.org/haskell-symposium/1999/1999-28.pdf> https://www.researchgate.net/publication/22156298safeobservablesharing_in_Haskell

Accelerate Accelerate is a data-parallel array language deeply embedded within Haskell. Accelerate internally uses tuples to represent types, which are stored in an struct-of-array fashion. Sum types are currently represented as a non-compact tagged union. Research has been done on a compact tagged union representation for parallel arrays, which has been named a *Recursive Tagged Union*[33]. The representation uses a unified tag for nested sum types, which optimizes memory usage at the cost of tag (de-)construction. It has not yet been implemented in Accelerate.

Futhark is a functional structurally typed data-parallel array language. Research has been done on including structural sum types to the Futhark compiler[30], which has been implemented. A sum type

is flattened to a tuple, which is stored as a struct-of-arrays. Identical primitive types are *deduplicated* and share the same tuple slot.

As Accelerate is a domain-specific-language within Haskell...

The `Elt` type-class (Extract, Load, Transform) defines a mapping between the Haskell and the Accelerate datatype. This process has been streamlined through a *generic* default implementation, which utilizes a standardized mapping. Functions do not use this process, and instead operate directly on the corresponding datatype.

Motivation A generic performant implementation is explored, which can alter between the representations. An implementation will be done in Accelerate, a data-parallel language embedded within Haskell.

Contributions

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