Home / Implementation



Implementation

** Warning: this section still needs to be updated for version 2.0 **

Index notation and the @tensor macro

We start by describing the implementation of the @tensor and @tensoropt macro. The macros end up transforming the index expression to the corresponding function calls to the primitive building blocks, which are discussed in the next section. In principle, anyone interested in making the @tensor macro work for custom array types should only reimplement these building blocks, but it is useful to understand how the tensor expressions are processed.

Tensors, a.k.a indexed objects

The central objects in tensor expressions that follow the @tensor macro are the index expressions of the form A[a,b,c]. These are detected as subexpressions of the form Expr(:ref, args). In fact, what is recognized by @tensor as an indexed object is more general, and also includes expressions of the form A[a b c] or A[a b; c d e] (Expr(:typed_hcat, args) and Expr(:typed_vcat, args)). The last form in particular is useful in more general contexts, and allows to distinguish between two sets of indices, referred to as left (a and b) and right (c, d and e) indices. This can be used when the @tensor macro wants to be generalized to user types, which for example distinguish between contravariant (upper) and covariant (lower) indices. For AbstractArray subtypes, such distinction is of course meaningless.

Note that the object being indexed, i.e. A in all of the above examples or args[1] in the corresponding Expr objects, can itself be an expression, that is not further analyzed. In particular, this may itself contain further indexing objects, such that one can get tensor objects from a list, e.g. list[3][a,b,c] or slice an array before using it in the @tensor expression, e.g. A[1:2:end,:,3:end][a,b,c].

Everything appearing in the [], e.g. args[2:end] (in case of :ref or :typed_hcat, the argument structure of :typed_vcat is slightly more complicated) is considered to be a valid index. This can be any valid Julia variable name, which is just kept as symbol, or any literal integer constant, (for legacy reasons, any literal character constant,) or finally an Expr(Symbol("'"), args), i.e. an expression of the form : (a'). The latter is converted to a symbol of the form Symbol("a'") when a is itself a symbol or integer, or this is applied recursively if a contains more primes.

The implementation for detecting tensors and indices (istensor, isindex) and actually converting them to a useful format (maketensor, makeindex) are found in src/indexnotation/tensorexpressions.jl.ln

particular, maketensor will return the indexed object, which is just esc(args[1]), the list of left indices and the list of right indices.

Furthermore, there is isscalar and makescalar to detect and process subexpressions that will evaluate to a scalar. Finally, there is isgeneral tensor and makegeneral tensor to detect and process a a tensor (indexed object), that is possibly conjugated or multiplied with a scalar. This is useful because the primitive tensor operations (i.e. see Building blocks below), accept a scalar factor and conjugation flag, so that these operations can be done simultaneously and do not need to be evaluated at first (which would require additional temporaries). The function makegeneral tensor in particular will return the indexed object, the list of left indices, the list of right indices, the scalar factor, and a flag (Boo1) that indicates whether the object needs to be conjugated (true) or not (false).

The file src/indexnotation/tensorexpressions.jl also contains simple methods to detect assignment
(isassignment) into existing objects (i.e. =, += and -=) or so-called definitions (isdefinition), that create
a new object (via := or its Unicode variant =, obtained as \coloneq + TAB). The function getlhsrhs will
return the left hand side and right hand side of an assignment or definition expression separately.

Finally, there are methods to detect whether the right hand side is a valid tensor expression (istensorexpr) and to get the indices of a complete tensor expressions. In particular, getindices returns a list of indices that will remain after the expression is evaluated (i.e. any index that is not contracted in the expression because it only appears once), whereas getallindices returns a list of all indices that appear in the expression. The latter is used to analyze complete tensor contraction graphs.

The macros @tensor and @tensoropt

Actual processing of the complete expression that follows the @tensor macro and converting it into a list of actual calls to the primitive tensor operations is handled by the functions defined in src/indexnotation/tensormacro.jl. The integral expression received by the @tensor macro is passed on to the tensorify function. The @tensoropt macro will first generate the data required to optimize contraction order, by calling optdata. If no actual costs are specified, i.e. @tensoropt receives a single expression, then optdata just assigns the same cost to all indices in the expression. Otherwise, the expression that specifies the costs need to be parsed first (parsecost). Finally, @tensoropt also calls tensorify passing the optdata as a second optional argument (whose default value nothing is used by @tensor).

The function tensorify consists of several steps. Firstly, it canonicalizes the expression. Currently, this involves a single pass which expands all conj calls of e.g. products or sums to a conj call on each of the arguments (via the expandconj function). Secondly, tensorify will process the contraction order using processcontractorder. This starts from the fact that a product of several tensors, specified as A[...]*B[...]*C[...] yields a single Expr(:call,[:*,...]) object where all the factors are still together. If a user wants a specific order, he can do so by grouping them with parenthesis. Whenever an expression Expr(:call,[:*,...]) is found where more than two of the arguments satisfy

isgeneral tensor, process contractorder will convert it into a nested set of pairwise multiplications according to a number of strategies discussed in the next subsection.

The major part of tensorify is to generate the correct function calls corresponding to the tensor expression. It detects assignments or definitions (the most common case) and validates the left hand side thereof (i.e. it should satisfy istensor and have no duplicate indices). Then, it generates the corresponding function calls corresponding to the index expression by passing onto the deindexify function, which takes the signature julia deindexify(dst, β , ex, α , leftind, rightind, istemporary = false) Here, dst is the symbol or expression corresponding to the destination object; it's nothing in case of a definition (:=), i.e. if the object corresponding to the result needs to be created/allocated. β and α are isscalar expressions, and deindexify will create the function calls required to update dst with multiplying dst with β and adding α times the result of the expression ex to it; this is supported as a one step process by each of the primitive operations. leftind and rightind correspond to the list of indices of the left hand side of the defition or assignment. The final argument istemporary indicates, if dst == nothing and a new object needs to be created/allocated, whether it is a temporary object. If istemporary == true, it can be stored in the cache and later retrieved. If istemporary == false, it corresponds to an explicit left hand side created by the user in a definition, and should not be in the cache.

The function deindexify will determine the top level operation represented by ex (which should be a istensorexpr), and then pass on to deindexify_generaltensor, deindexify_linearcombination, deindexify_contraction for actually creating the correct function call expressions. If any of the arguments of e.g. a linear combination or a tensor contraction is itself a composite tensor expression (i.e. not a isgeneraltensor), deindexify is called recursively.

Analyzing contraction graphs (a.k.a tensor networks) and optimizing contraction order

The function processcontractorder, which is excuted before the index expression is converted to function calls, will detect any multiplication with more than two isgeneraltensor factors, and divide it up into a nested sequence of pairwise multiplications (tensor contractions), i.e. a tree. If the @tensor macro was used, optdata = nothing and in principle the multiplication will be performed from left to right. There is one exception, which is that if the indices follow the NCON convention, i.e. negative integers are used for uncontracted indices and positive integers for contracted indices. Then the contraction tree is built such that tensors that share the contraction index which is the lowest positive integer are contracted first. Relevant code can be found in src/indexnotation/ncontree.jl

When the @tensoropt macro was used, optdata is a dictionary associating a cost (either a number or a polynomial in some abstract scaling parameter) to every index, and this information is used to determine the (asymptotically) optimal contraction tree (in terms of number of floating point operations). The code for the latter is in src/indexnotation/optimaltree.jl, with the lightweight polynomial implementation in src/indexnotation/polynomial.jl. Aside from a generic polynomial type Poly, the latter also contains

a Power type which represents a single term of a polynomial (i.e. a scalar coefficient and an exponent). This type is closed under multiplication, and can be multiplied much more efficiently. Only under addition is a generic Poly returned.

Building blocks

The @tensor macro converts the index expression into a set of function calls corresponding to three primitive operations: addition, tracing and contraction. These operations are implemented for arbitrary strided arrays from Julia Base, i.e. Arrays, views with ranges thereof, and certain reshape operations. This includes certain arrays that can only be determined to be strided on runtime, and does therefore not coincide with the type union StridedArray from Julia Base. In fact, the methods accept AbstractArray objects, but convert these to (Unsafe)StridedView objects from the package Strided.jl, and we refer to this package for a more detailed discussion on which arrays are supported and why.

The primitive tensor operations are captured by the following mutating methods (note that these are not exported)

TensorOperations.add! — Function

```
add!(\alpha, A, conjA, \beta, C, indleft, indright)
```

Implements $C = \beta*C+\alpha*permute(op(A))$ where A is permuted such that the left (right) indices of C correspond to the indices indleft (indright) of A, and op is conj if conj A == :C or the identity map if conj A == :N (default). Together, (indleft..., indright...) is a permutation of 1 to the number of indices (dimensions) of A.

TensorOperations.trace! — Function

```
trace!(α, A, conjA, β, C, indleft, indright, cind1, cind2)
```

Implements $C = \beta*C+\alpha*partialtrace(op(A))$ where A is permuted and partially traced, such that the left (right) indices of C correspond to the indices indleft (indright) of A, and indices cindA1 are contracted with indices cindA2. Furthermore, op is conj if conj A == :C or the identity map if conj A =: N (default). Together, (indleft..., indright..., cind1, cind2) is a permutation of 1 to the number of indices (dimensions) of A.

TensorOperations.contract! — Function

 $contract!(\alpha, A, conjA, B, conjB, \beta, C, oindA, cindA, oindB, cindB, indleft, indrig$

Implements $C = \beta*C+\alpha*contract(opA(A), opB(B))$ where A and B are contracted, such that the indices cindA of A are contracted with indices cindB of B. The open indices oindA of A and oindB of B are permuted such that C has left (right) indices corresponding to indices indleft (indright) out of (oindA..., oindB...). The operation opA (opB) acts as conj if conjA (conjB) equal :C or as the identity map if conjA (conjB) equal :N. Together, (oindA..., cindA...) is a permutation of 1 to the number of indices of A and (oindB..., cindB...) is a permutation of 1 to the number of indices of C. Furthermore, length(cindA) == length(cindB), length(oindA)+length(oindB) equals the number of indices of C and (indleft..., indright...) is a permutation of 1 of the number of indices of C.

The final argument syms is optional and can be either nothing, or a tuple of three symbols, which are used to identify temporary objects in the cache to be used for permuting A, B and C so as to perform the contraction as a matrix multiplication.

These are the central objects that should be overloaded by custom tensor types that would like to be used within the @tensor environment. They are also used by the function based methods discussed in the section Functions.

Furthermore, it is essential to be able to construct new tensor objects that are similar to existing ones, i.e. to place the result of the computation in case no output is specified. In order to reuse temporary objects stored in the global cache, this method also receives a candidate similar object, which it can return if it matches the requirements.

Missing docstring.

Missing docstring for TensorOperations.checked_similar_from_indices.Check Documenter's build log for details.

Note that the type of the cached object is not known to the compiler, as the cache stores objects as Any. Therefore, the function <code>checked_similar_from_indices</code> should try to restore the type information. By passing any object retrieved from the cache through this function, type stability within the <code>@tensor</code> macro can then still be guaranteed.

Finally, there is a particularly simple method scalar whose sole purpose is to extract the single entry of an object with zero indices, i.e. an instance of AbstractArray{T,0} in case of Julia Base arrays:

scalar(C)

Returns the single element of a tensor-like object with zero indices or dimensions.

The implementation of all of these methods can be found in src/implementation/stridedarray.jl.

By implementing these five methods for other types that represent some kind of tensor or multidimensional object, they can be used in combination with the @tensor macro. In particular, we also provide basic support for contracting a Diagonal matrix with an arbitrary strided array in src/implementation/diagonal.jl

« Cache for temporaries

Powered by Documenter.jl and the Julia Programming Language.