

An Execution Abstraction for Compact Computational Kernels on Unstructured Meshes

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Chapter 1

Introduction

The remainder of this paper is laid out as follows...

Chapter 2

Background

Before a discussion of `pyop3`, it is useful to review some of the relevant background material. We will first provide a mathematical motivation for mesh execution models using a common operation, *finite element assembly*, as an example. Then we will review...Finally, we describe in more detail the core pieces of software that `pyop3` bases its abstractions upon: PyOP2, numpy and PETSc DMPlex.

2.1 The finite element method

For a non-trivial example for when mesh loops (?) are required, we consider solving the Stokes equations using the finite element method (FEM). Our exposition will focus on the aspects of the computation that are relevant for `pyop3`, for a more complete review of FEM we refer the reader to [4] and [9].

The Stokes equations are a linearisation of the Navier-Stokes equations and are used to describe fluid flow for laminar (slow and calm) media. For domain Ω and boundary Γ , omitting any viscosity or forcing terms for simplicity, they are given by

$$-\Delta u + \nabla p = 0 \quad \text{in } \Omega, \tag{2.1a}$$

$$\nabla \cdot u = 0 \quad \text{in } \Omega, \tag{2.1b}$$

$$u = g \quad \text{on } \Gamma. \tag{2.1c}$$

with u the fluid velocity and p the pressure. We also prescribe Dirichlet boundary conditions for the velocity across the entire boundary, setting u to the value of function g . Since we have a coupled system of two variables (u and p), we refer to the Stokes system as being a *mixed* problem.

2.1.1 Deriving a weak formulation

For the finite element method we seek the solution to the *variational*, or *weak*, formulation of these equations. These are obtained by multiplying each equation by a suitable *test function* and integrating over the domain. For eq. (2.1), using v and q as the test functions, drawn from function spaces \hat{V} and Q respectively, and integrating by parts this gives

$$\int \nabla u : \nabla v \, d\Omega - \int p \nabla \cdot v \, d\Omega - \int (\nabla u \cdot n) \cdot v \, d\Gamma - \int p n \cdot v \, d\Gamma = 0 \quad \forall v \in \hat{V} \quad (2.2a)$$

$$\int q \nabla \cdot u \, d\Omega = 0 \quad \forall q \in Q. \quad (2.2b)$$

From these weak forms it is now possible to classify the function spaces for u and p . For u , we already know that the space must be vector-valued, since it stores a velocity, and constrained to g on the boundary. Equation (2.2a) further shows us that u must have at least one weak derivative. We can therefore say that $u \in V$ where

$$V = \{ v \in [H^1(\Omega)]^d : v|_{\Gamma} = g \}$$

p is scalar-valued, no derivatives of p are present in the weak formulation, nor are any boundary conditions applied to it and so we can write that $p \in Q$ where

$$Q = \{ q \in L^2(\Omega) \}$$

Since the values of u at the boundary are already prescribed, the function space of the test function v is defined to be zero at those nodes

$$\hat{V} = \{ v \in [H^1(\Omega)]^d : v|_{\Gamma} = 0 \}.$$

This allows us to drop some terms from eq. (2.2a), allowing us to state the final problem as follows:

Find $(u, p) \in V \times Q$ such that

$$\int \nabla u : \nabla v \, d\Omega - \int p \nabla \cdot v \, d\Omega = 0 \quad \forall v \in \hat{V} \quad (2.3a)$$

$$\int q \nabla \cdot u \, d\Omega = 0 \quad \forall q \in Q. \quad (2.3b)$$

2.1.2 Discretising the system of equations

In order to solve this weak formulation using the finite element method we discretise the function spaces in use by replacing them with a finite dimensional equivalent:

$$V \rightarrow V_h \subset V, \quad \hat{V} \rightarrow \hat{V}_h \subset \hat{V}, \quad Q \rightarrow Q_h \subset Q.$$

Each of these discrete spaces is spanned by a set of basis functions so any function can be expressed as a linear combination of the basis functions and their coefficients. For example, we can write the function $u_h \in V_h$ as

$$u_h = \sum_{i=1}^N \hat{u}_i \psi_i^{V_h}$$

for basis functions $\psi_i^{V_h}$ and coefficients \hat{u}_i .

Substituting these discrete function spaces back into eq. (2.3), and discarding the basis coefficients for the arbitrary functions v_h and q_h , we obtain the discrete problem:

Find (\hat{u}, \hat{p}) such that

$$\int \hat{u} \nabla \psi^{V_h} : \nabla \psi^{\hat{V}_h} \, d\Omega - \int \hat{p} \psi^Q \nabla \cdot \psi^{\hat{V}_h} \, d\Omega = 0 \quad \forall \psi^{\hat{V}} \quad (2.4a)$$

$$\int \psi^Q \nabla \cdot \hat{u} \psi^{V_h} \, d\Omega = 0 \quad \forall \psi^Q \quad (2.4b)$$

This can be reformulated as the (saddle point) linear system

$$\left(\begin{array}{c|c} \int \nabla \psi^{V_h} : \nabla \psi^{\hat{V}_h} \, d\Omega & - \int \psi^Q \nabla \cdot \psi^{\hat{V}_h} \, d\Omega \\ \hline \int \psi^Q \nabla \cdot \psi^{V_h} \, d\Omega & 0 \end{array} \right) \begin{pmatrix} \hat{u} \\ \hat{p} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \quad (2.5)$$

Solving the Stokes equations using the finite element method therefore boils down to constructing, or *assembling*, the left-hand-side matrix and the, here trivial, right-hand-side vector before solving for the coefficients \hat{u} and \hat{p} .

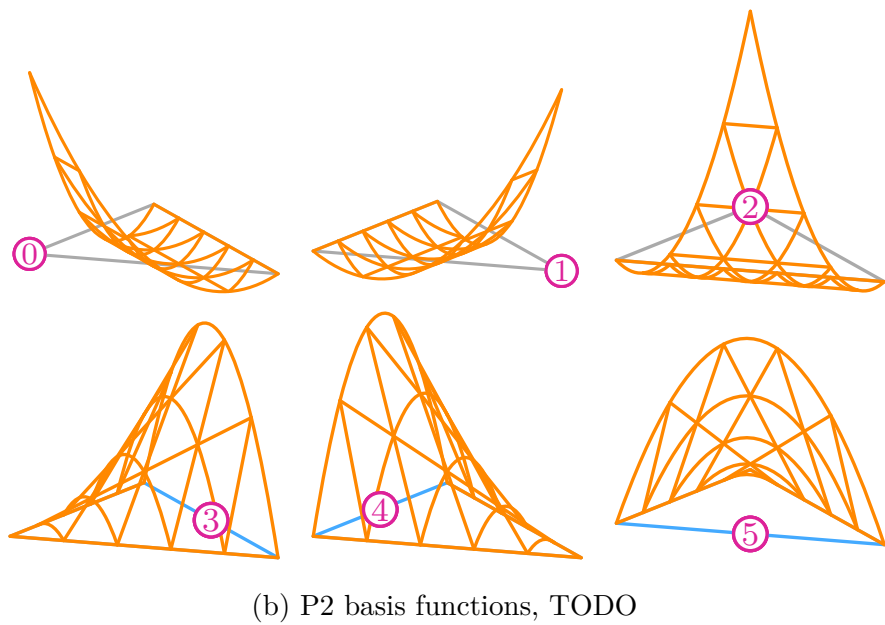
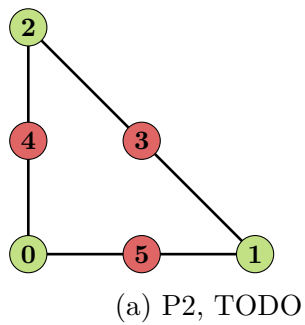


Figure 2.1: TODO, [11]



Figure 2.2: Scott-Vogelius element (degree 3?)

All																								
Fields	V_h												Q_h											
Points	v_0	v_1	v_2	e_0	e_1	e_2	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0	c_0
Nodes	0	1	2	3	4	5	6	7	8	9	0	1	2	3	4	5	6	7	8	9	0	1	2	3
DoFs	0_0	0_1	1_0	1_1	2_0	2_1	3_0	3_1	4_0	4_1	5_0	5_1	6_0	6_1	7_0	7_1	8_0	8_1	9_0	9_1	0	1	2	3

Figure 2.3: TODO

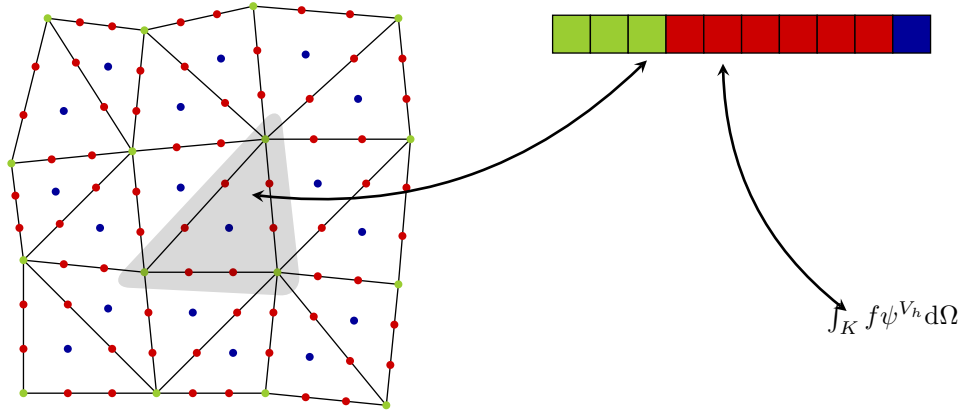


Figure 2.4: TODO

2.1.3 Choosing a finite element pair

2.1.4 The assembly algorithm

2.2 Code generation and domain-specific languages for scientific computing

[12] [10] [1]

2.2.1 Abstractions for array computations

2.2.2 Abstractions for mesh-like data layouts

Taichi is a programming language embedded in C for operating on complex data structures [5]. Just like **pyop3**, Taichi declares data structures hierarchically and the data layout is kept distinct from the operations applied to them. Taichi has no concept of a mesh, and it does not work on distributed machines.

2.3 An abstraction for unstructured meshes: PETSc DM-Plex

2.4 An execution model: PyOP2

2.4.1 An interface for multi-dimensional data: numpy

Chapter 3

Mesh-like data layouts

`pyop3` was created to provide a richer abstraction than `PyOP2` for describing stencil-like operations over unstructured meshes. Most of the innovation in `pyop3` stems from its novel data model. Data structures associated with a mesh are created using more information about the mesh topology. This lays the groundwork for a much more expressive DSL since more of the semantics are captured/represented.

The semantics for data kept on a mesh are not accurately captured by existing array abstractions.

Classic existing abstractions include N-dimensional array, ragged arrays and struct-of-arrays.

To provide a motivating example, consider the mesh shown in fig. 3.1. Degree 3 Lagrange elements have been used and these have 1 DoF per vertex, 2 per edge and 1 per cell. DoFs are always stored contiguously per mesh point, and so the data layout for this mesh would look something like that shown in ???. It is clear that, due to the variable step size for each mesh point, an N-dimensional array (with $N > 1$) is a poor fit for describing the layout. One could also view the data as just a flat array (figure ZZZ), but this loses the information about the mesh points.

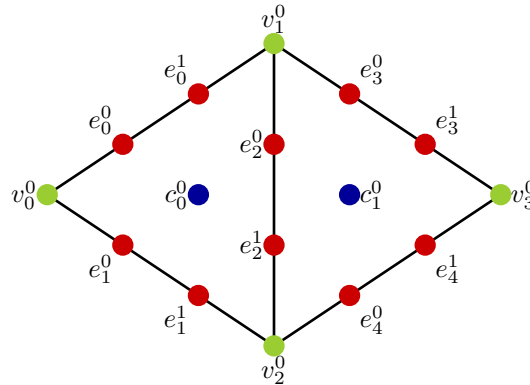


Figure 3.1: TODO

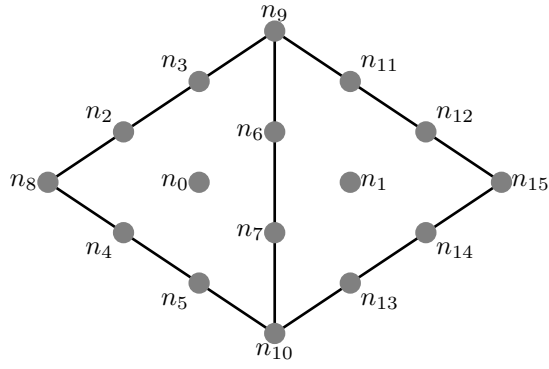


Figure 3.2: TODO

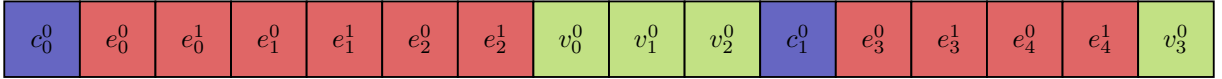


Figure 3.3: TODO

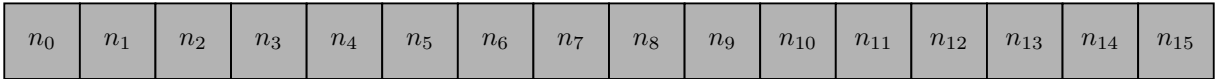


Figure 3.4: TODO

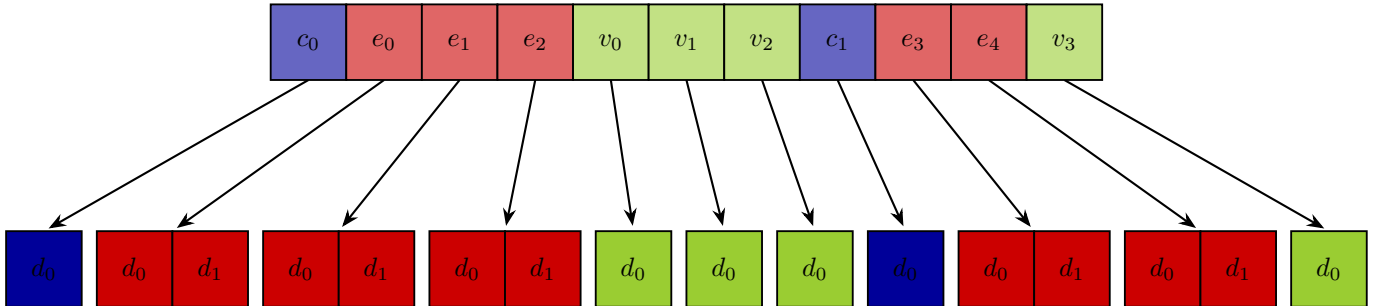
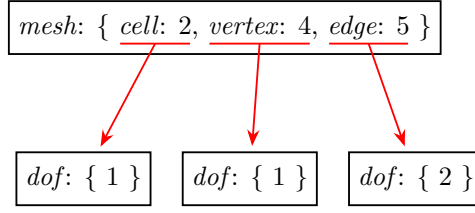


Figure 3.5: TODO



(a) TODO. For simplicity the component labels for the *dof* sub-axes have been omitted.

```
axes = AxisTree.from_nest({
    Axis({"cell": 2, "vertex": 4, "edge": 5}, "mesh"): [
        Axis(1, "dof"), # cell DoFs
        Axis(1, "dof"), # vertex DoFs
        Axis(2, "dof"), # edge DoFs
    ]
})
```

(b) TODO

Figure 3.6: The axis tree representing the data layout for mesh data corresponding to that shown in fig. 3.1. Note that the data has not been reordered here (see section 3.2).

We can therefore conclude that mesh data layouts require a new abstraction for comprehensively describing their semantics: *axis trees*.

3.1 Axis trees

From ?? it can be observed that the data layout naturally decomposes into a tree-like structure. For every class of topological entity (i.e. vertex, edge or cell) there is a distinct number of DoFs associated with it.

Typically, this structural information is discarded. `pyop3`, however, is capable of capturing this information through using the concept of an *axis tree*.

And axis tree is composed of a hierarchy of *axes*, and each axis has one or more *axis components*. Each axis may either be the *root* axis, with no parent, or it has a parent consisting of the 2-tuple (parent axis, parent component). In other words each subaxis is attached to a particular axis, component pair like, say, the cells of a mesh.

To uniquely identify axes and components, they are both equipped with a *label*. With these labels, one can uniquely describe a particular *path* going down the tree from root to leaf. To give an example from fig. 3.6a, one could select the DoFs associated with the edges by passing the path (as a mapping): { "mesh": "edge", "dof": None }. The keys of the mapping are the axis

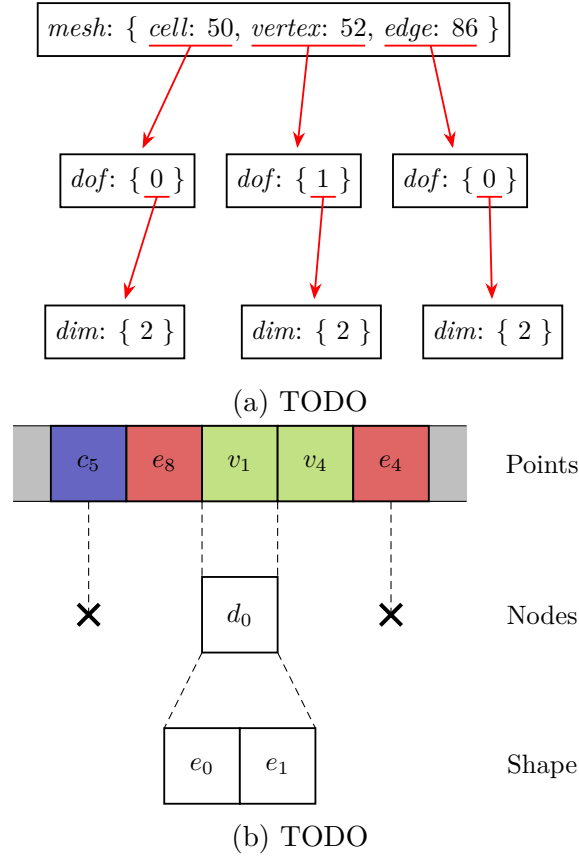


Figure 3.7: TODO

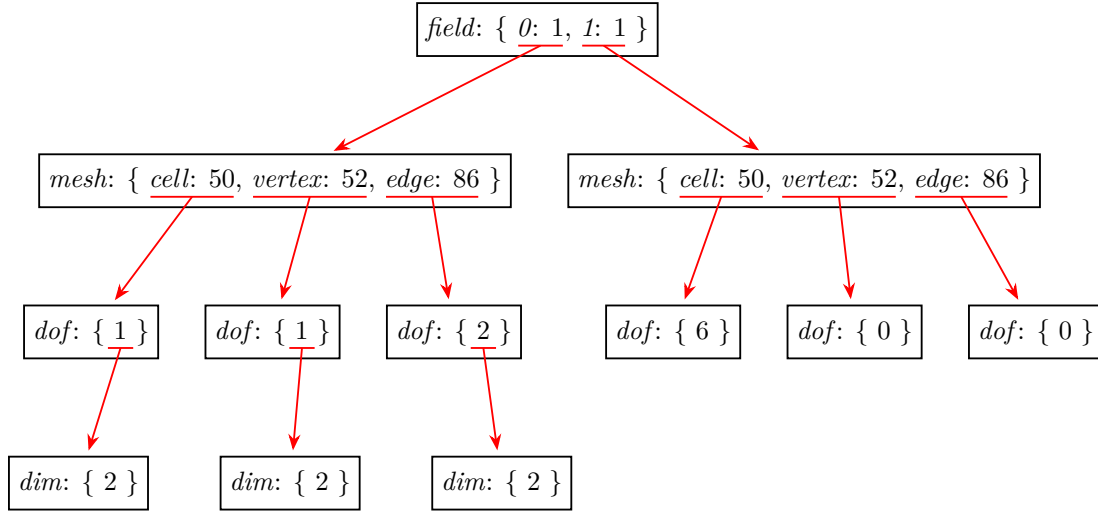
labels and the values are the component labels. **None** is permissible for the "dof" axis because there is only a single component, and hence no ambiguity. Axis component labels must be unique within an axis, and axis labels must be unique within each possible path leading from root to leaf.

The notion of an *axis* has already been well established by numpy. If we consider a 3-dimensional numpy array with shape (3, 4, 5), each dimension of the array is considered to be an axis. One can for instance change the order in which the array is traversed by specifying the axes via a `transpose` call (e.g. `numpy.transpose(array, (2, 0, 1))`).

3.1.1 Examples

Vector-valued function spaces

This approach naturally extends to tensor-valued function spaces, where the multiple inner axes may be provided to represent, for example, a small 3×3 matrix stored for every mesh point.



(a) TODO

Mixed function spaces

In exactly the same way as for vector-/tensor-valued function spaces, the order in which the axes are declared is flexible...

3.2 Renumbering for data locality

For memory-bound codes, performance is synonymous with data locality. In the case of stencil codes like finite element assembly, one should aim to arrange the data such that the data required for a single stencil calculation is contiguous in memory and can be read from memory into cache with only a single instruction.

For simulations involving unstructured meshes, data reorderings that provide perfect streaming access to memory are not possible and so renumbering strategies have been developed to try and maximise locality. For example, the data layout shown in fig. 3.3 approximates the strategy taken by PyOP2, cells are traversed according to some RCM ordering and the cell closures are packed next to the cell [8]. This is effective for finite element codes because finite element assembly (usually) involves iterating over cells and accessing the data in their closures.

In `pyop3`, we choose a simple approach and defer to PETSc to provide us with an appropriate RCM numbering for the points. This is communicated to the axis tree by giving an axis, in this case the `"mesh"` one, a `numbering` argument. This numbering consists of the flat indices of the axis and is exactly the object given to us from PETSc. This is not quite the case in parallel (see chapter 6).

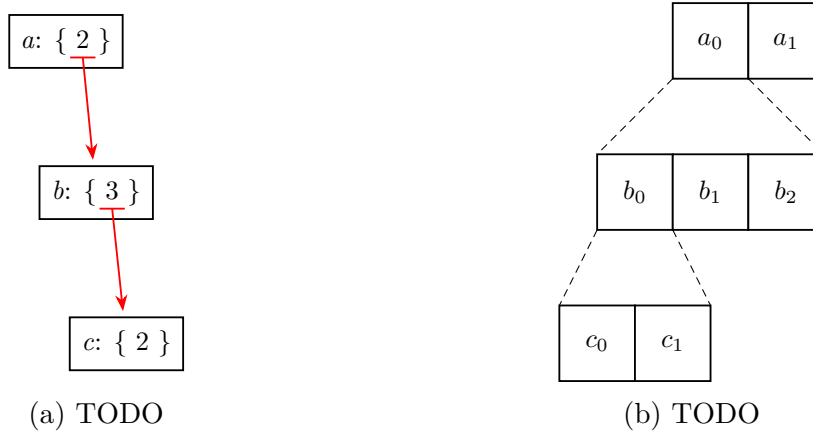


Figure 3.9: TODO

3.3 Ragged arrays

3.4 Computing offsets

In the same way that the shape of a numpy array describes how to stride over a flat array, axis trees are simply data layout descriptors that declare how one accesses an ultimately flat array. Indeed, in `pyop3` (flat) numpy arrays are used as the underlying data structure. It is the job of the axis tree to provide the right expression that can be evaluated giving the correct offset into the flat array.

In `pyop3`, axis trees are traversed to produce *layout functions*. These are symbolic expressions of zero or more indices that can be evaluated to give the correct offset into the underlying array. Layout functions, expressed in the symbolic maths package *pymbolic*¹, may either be evaluated given a set of indices or used during code generation.

To give a simple example, consider the axis tree and corresponding data layout shown in fig. 3.9. The tree shown here is equivalent to a numpy array with shape (2, 3, 2) with the numpy axes 0, 1 and 2 given the labels *a*, *b* and *c* respectively. Given a multi-index of the form (i_a, i_b, i_c) the correct offset into the array may be calculated with the layout function $6i_a + 2i_b + i_c$.

¹<https://document.tician.de/pymbolic/index.html>

3.4.1 The layout algorithm, step by step

The algorithm can be deconstructed into two stages:

1. Determine the right expression for describing the layout of each axis component separately.
For the linear axis tree shown in fig. 3.9 this corresponds to determining the expressions $6i_a$, $2i_b$ and i_c .
2. Add the component-wise layout expressions together.

Of these, the former stage is by far the most complex and is the one that will be explained in more detail below.

In the following we will incrementally describe the algorithm for determining the right layout function for a given axis tree.

There are additional considerations in parallel that are discussed later in chapter 6.

Linear axis trees

Algorithm 1 Algorithm for computing the layout functions of a linear (single component) axis tree such as that shown in fig. 3.9a. The function is initially invoked by passing the root axis of the tree.

```
1 def tabulate_layouts_linear(axis: Axis):
2     layouts = {}
3
4     # post-order traversal
5     if has_subaxis(axis):
6         subaxis = get_subaxis(axis)
7         layouts |= tabulate_layouts_linear(subaxis)
8
9     # layout expression for this axis
10    if has_subaxis(axis):
11        step = get_subaxis_size(axis)
12    else:
13        step = 1
14    layouts[axis] = AxisVar(axis) * step
15
16    return layouts
```

We begin our exposition with the simplest possible case: “linear” axis trees. A “linear” tree means that the axes in the tree are restricted to be single component. Such trees are directly equivalent to numpy-like N-dimensional arrays or *tensor* objects in many domain-specific programming languages. An example of such a tree and data layout is shown in fig. 3.9.

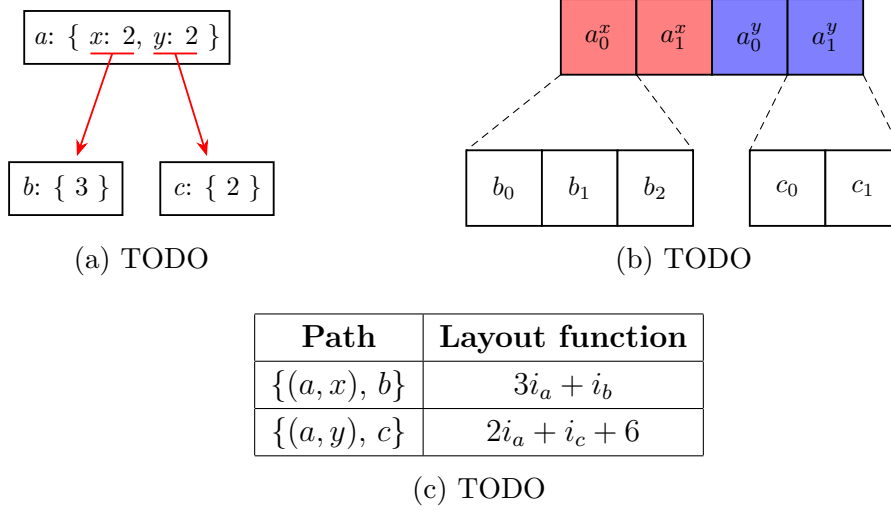


Figure 3.10: TODO

Pseudocode for determining the right layout function for a linear axis tree is shown in algorithm 1. The axis tree is traversed in a post-order fashion with subaxes handled first (the reason for this is made clear in section 3.4.1). At each axis, since we only require affine expressions, the layout function is simply the symbolic expression `AxisVar(axis) * step`, where `AxisVar(axis)` is a symbolic `Variable` object and `step` is an integer corresponding to the size of the subtree as seen from that axis.

Multi-component axis trees

When multi-component axis trees are introduced, a number of things change: First, there are now multiple layout functions per axis. This is one per `(axis, component)` pair. Second, the affine indexing used in the linear case above must now also include offsets.

This is shown in fig. 3.10. The root axis of the axis tree now has two components, given the labels x and y , each with their own subaxis (labelled b and c). The layouts of the (a, x) part of the tree are effectively unchanged from the linear case, but the y component of axis a now clearly carries an offset. This is shown in the layout functions in fig. 3.10c.

The modifications from algorithm 1 required to determine the right layout function for a multi-component axis tree are relatively straightforward. The modified algorithm is shown in algorithm 2 with the core changes labelled and highlighted in red. These core changes are:

- A** The post-order traversal must now be over *per-component* subaxes, so a loop over axis components is required.
- B** The layout functions are now stored per `(axis, component)` pair, and an additional offset, named `start`, is added.

Algorithm 2 Algorithm for computing the layout functions of an axis tree where any of the contained axes may have multiple components.

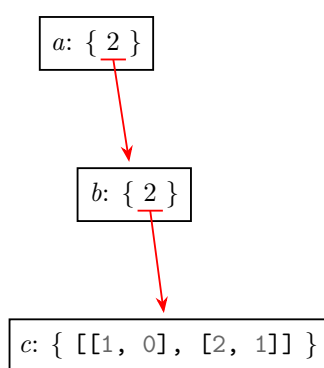
```

1  def tabulate_layouts_multi_component(axis: Axis):
2      layouts = {}
3
4      # post-order traversal
5      for component in axis.components:
6          if has_subaxis(axis, component):
7              subaxis = get_subaxis(axis, component)
8              layouts |= tabulate_layouts_multi_component(subaxis)
9
10     # layout expressions for this axis
11     start = 0
12     for component in axis.components:
13         if has_subaxis(axis, component):
14             step = get_subaxis_size(axis, component)
15         else:
16             step = 1
17         layouts[(axis, component)] = AxisVar(axis) * step + start
18         start += step
19
20     return layouts

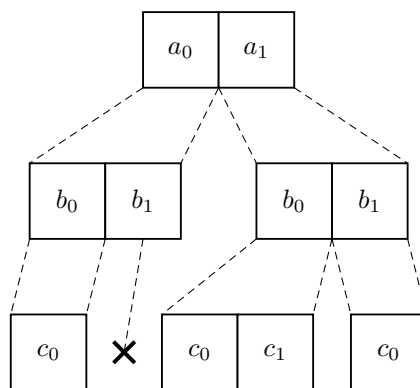
```

} A

} B



(a) TODO



(b) TODO

Path	Layout function
$\{a, b, c\}$	$[[0, 1], [1, 3]]_{i_a, i_b} + i_c$

(c) TODO

Figure 3.11: TODO

Ragged axis trees

Algorithm 3 Algorithm for computing the layout functions of an axis tree where any of the contained axes may be ragged.

```
1 def tabulate_layouts_ragged(axis: Axis):
2     layouts = {}
3
4     # post-order traversal
5     for component in axis.components:
6         if has_subaxis(axis, component):
7             subaxis = get_subaxis(axis, component)
8             sublayouts, subtree = tabulate_layouts_ragged(subaxis)
9             layouts |= sublayouts
10
11     # layout expressions for this axis
12     start = 0
13     for component in axis.components:
14         if has_subaxis(axis, component):
15             step = get_subaxis_size(axis, component)
16         else:
17             step = 1
18         layouts[(axis, component)] = AxisVar(axis) * step + start
19         start += step
20
21     return layouts
```

Chapter 4

Indexing

In array codes it is very rarely the case that the entire array is operated on as a single unit. Instead, what more commonly happens is the array is restricted to a smaller piece (e.g. a single value) so that it may be read or modified. This operation is almost universally referred to as *array indexing*. In this chapter we introduce the necessary abstractions and algorithms required to index axis trees in `pyop3`.

4.1 A primer: indexing numpy arrays

Just as axis trees can be regarded as a generalisation of numpy arrays, indexing arrays in `pyop3` is, as far as possible, analogous to indexing operations in numpy. Before diving into how `pyop3` does things it is therefore instructive to review how indexing is done in numpy.

Some of the ways that a numpy array may be indexed are shown in table 4.1:

- **Single element indexing**

Single element indexing takes an integer and simply returns the value stored at that point.

- **Slicing**

Index operation	Example	Return value	Array return type
Single element indexing	<code>array[1]</code>	"B"	N/A
Slicing	<code>array[1:6:2]</code>	["B", "D", "F"]	View
Integer array indexing	<code>array[[0, 3, 4]]</code>	["A", "D", "E"]	Copy

Table 4.1: Common indexing operations for numpy arrays. The examples shown apply the index to the string array ["A", "B", "C", "D", "E", "F"] (called `array` above). The array return type for single element indexing is marked as “N/A” because a string is returned instead of an array.

Slices are a standard Python concept for describing ranges of indices and have the syntax `[start:stop:step]`. Omitting `start`, `stop` or `step` will default to 0, the end of the array, and 1 respectively. In the example shown in table 4.1 the slice `[1:6:2]` corresponds to asking for “the values in the array from index 1 (inclusive) to index 6 (exclusive), striding by 2”.

- **Integer array indexing**

Integer array indexing returns a new array containing values stored at the requested indices, for the example in table 4.1 this simply being 0, 3 and 4.

Although the examples provided are all for a 1-dimensional array, it is completely permissible to index N-dimensional arrays with a collection of these indexing operations, one per axis of the array.

numpy draws a distinction between “basic” indexing, single element indexing and slicing, and “advanced” indexing like using integer arrays. For the former, the array returned from the indexing operation is a *view*, whereas for the latter a *copy* is returned. Alongside the obvious memory advantages, views are also preferable to copies because they are *composable*. One can take views of views repeatedly without triggering a copy, allowing for changes to the indexed array to be propagated back to the original. In `pyop3`, as well as generalising the indexing operations above to axis trees, we overcome this shortcoming of numpy’s advanced indexing such that views are always used regardless of the indexing method used.

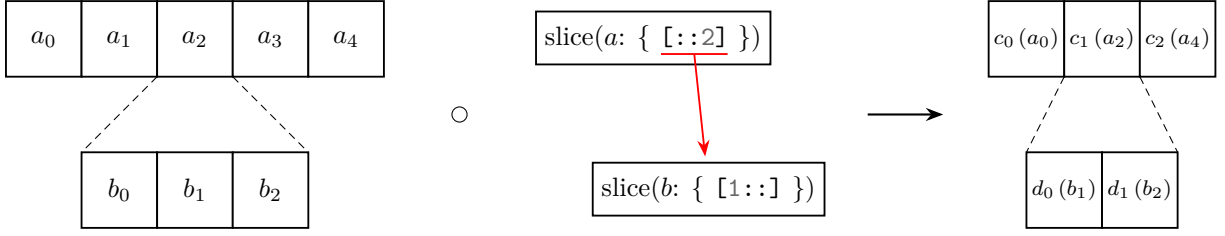
4.2 Index trees

In `pyop3`, indexing is accomplished via the use of *index trees*. Analogously to axis trees, index trees consist of multiple *index* objects, each of which has one or more *index components*. When an axis tree is indexed, it is transformed via composition with an index tree:

$$\text{Axis tree} \quad \circ \quad \text{Index tree} \quad \rightarrow \quad \text{Indexed axis tree}$$

This composition operation yields a new *indexed* axis tree that understand how its entries map back to the original axis tree. In other words, it is a *view*.

To illustrate this with a simple example, consider the indexing operation shown in fig. 4.1. It shows a slicing operation applied to a linear axis tree with shape `(5, 3)` and axes labelled *a* and *b*. The index tree is also linear and consists of two *slice* objects over the axes *a* and *b* respectively with the former taking every other entry in *a* (`[:, :2]`) and the latter taking all but the first entry in *b* (`[1: :]`). The indexed axis tree resulting from the composition of these trees is shown to the right: only the selected indices from axes *a* and *b* are present and the axes have been relabelled (arbitrarily) *c* and *d*.



(a) Diagram of the data layout transformation. The original axis tree (left) is composed with an index tree (middle) to produce a new, indexed, axis tree (right). The bracketed values in the final tree show the original array entries that they map to.

Source path	Target path	Target expressions
$\{c, d\}$	$\{a, b\}$	$\{i_a: 2i_c, i_b: i_d + 1\}$

(b) The indexing information carried by the transformed axis tree that allows it to map back to the original unindexed tree.

Figure 4.1: The axis tree transformation resulting from indexing a linear axis tree with shape $(5, 3)$ with slices $[:, :2]$ and $[1::]$ on axes a and b respectively. The resulting axis tree has shape $(3, 2)$ and different labels: c and d .

In addition to having a new shape and new labels, the indexed axis tree also carries the information necessary to map back from the indexed shape (the *source*) to the original axis tree (the *target*). This is done by associating two attributes with the indexed axis tree:

Target paths The target path is a map from the source tree to the axis labels of the target tree. It allows `pyop3` to know where the source axes came from so it can select the right layout functions (??) from the target tree. In fig. 4.1b, the target path is shown to be, for source path $\{a, b\}$, indicating that source axes c and d map back to a and b in the original array.

Target expressions For an indexed axis tree, the target expressions relate the source indices to the target indices as a distinct symbolic expression per target axis. In fig. 4.1b the two target expressions are shown to be $i_a := 2i_c$ and $i_b := i_d + 1$, telling us that c_m maps to a_{2m} and that d_n maps to b_{n+1} respectively.

With these two pieces of information, it is now possible to implement view-like semantics for indexed axis trees. One simply has to:

1. Use the target path to select the appropriate layout function from the target axis tree.
2. Modify the layout function by substituting the target indices in the function with the source indices as described by the target expressions attribute of the indexed tree.

3. Evaluate the offset using the new layout function (that is now a function of the source indices rather than the target indices).

Applying these steps using the indexing operation of fig. 4.1, we have:

1. The target path is $\{a, b\}$, so the selected layout function is $offset = 3i_a + i_b$.
2. Substituting the target expressions in fig. 4.1b, we get the new layout function $offset = 6i_c + i_d + 1$.
3. The original axis tree may now be addressed using the source indices i_c and i_d .

4.2.1 Indexed axis tree construction

Algorithm 4 Algorithm that constructs the necessary components to build an indexed axis tree by visiting the nodes of an index tree.

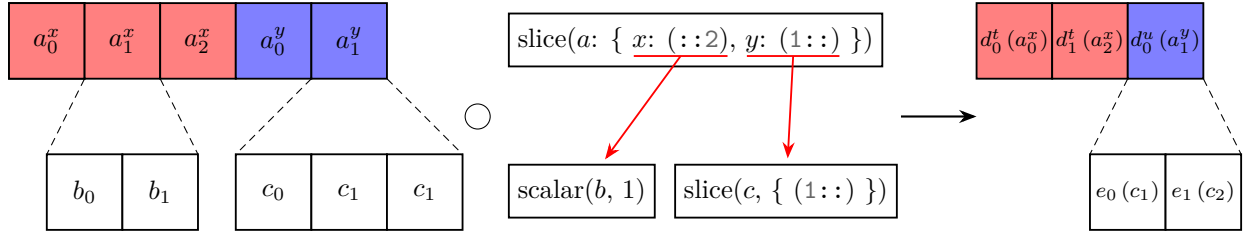
```

1  def index_axes(index, old_axis_tree):
2      # process the current index
3      axis_tree, target_paths, target_exprs = index_handler(index, old_axis_tree)
4
5      for component in index.components:
6          if has_subindex(index, component):
7              # recursively visit child indices
8              subindex = get_subindex(index, component)
9              subaxis_tree, subtarget_paths, subtarget_exprs = index_axes(subindex, old_axis_tree)
10
11             axis_tree.add_subtree(subaxis_tree)
12             target_paths |= subtarget_paths
13             target_exprs |= subtarget_exprs
14
15     return axis_tree, target_paths, target_exprs

```

The construction of an indexed axis tree from an axis tree and index tree is accomplished via a traversal of the index tree (algorithm 4). Each index of the tree is processed by the function `index_handler` (line XXX) to give an axis tree and set of targets paths and expressions specific to that index. These axis trees are then glued together (line YYY) to give the axis tree for the final object while the target paths and target expressions are similarly combined (lines AAA and BBB). Finally, once collected, the three returned variables may be used to construct a finished indexed axis tree.

The original axis tree (`old_axis_tree`) plays only a small role in the indexing algorithm. It is used to determine the sizes of sliced axes and consistency checks.



(a) Diagram of the data layout transformation. ...

Source path	Target path	Target expressions
-------------	-------------	--------------------

(b) The indexing information carried by the transformed axis tree that allows it to map back to the original unindexed tree.

Figure 4.2: TODO The axis tree transformation resulting from indexing a linear axis tree with shape $(5, 3)$ with the slices $::2$ and $(1::)$ on axes a and b respectively. The resulting axis tree has shape $(3, 2)$ and different labels: c and d .

4.2.2 Index composition

4.3 Outer loops

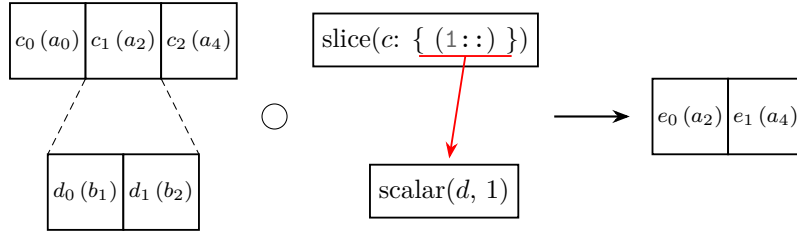
The indexing routines demonstrated so far are not sufficient for `pyop3`'s purposes. If we consider the prototypical finite element assembly loop (??) we see that there is an outer loop over cells, and that the data is packed, or indexed, *relative* to the current cell.

In `pyop3`, these outer loops are described by the `loop(...)` construct. Calling `loop` creates a *loop expression*, which is a symbolic object representing the loop to be performed. The loop expression expects a *loop index*, and a collection of *statements*. The loop index represents the domain to be iterated over and it has an associated axis tree where each element of the axis tree will be visited. The statements may be further loops or arbitrary operations (see ?? for a more in-depth description).

To give an example, one of the simplest possible loops that one can write in `pyop3` is shown in fig. 4.4a. Here the loop index (`i`) is simply “all elements of `dat`” and there is a single statement that sets each entry in `dat` to the arbitrary value of 666. Note that the syntax of the loop expression is deliberately similar to that of Python (or other imperative programming languages).

The challenge here is how to represent the indexing operation `dat[i]...`

Furthermore, the indexed object is dependent upon the loop index: the target expressions of the axis tree must reference the loop index. In `pyop3` we say that it is *context-dependent*.



(a) The index composition operation. All but the first (1::) of axis c is selected with only the second entry in axis d .

Source path	Target path	Target expressions
$\{e\}$	$\{a, b\}$	$\{i_a: 2(i_e + 1), i_b: 2\}$

(b) Index expressions and paths relating the indexed “source” tree back to the original unindexed tree. Note how the index for axis d (i_d) is not present among the target expressions as it has been substituted for a 1.

Figure 4.3: The composition of an already indexed axis tree (from fig. 4.1) with another index tree. Since a scalar index is used, the axis tree “loses shape” and is transformed from one with shape (3, 2) to one with shape (2,). The resulting axis tree can still be mapped correctly back to the original unindexed axis tree.

4.4 Maps

Maps differ from slices because they add additional shape. They have a from index

How to build a map.

4.4.1 Ragged maps

Ragged maps are also supported. e.g. support, star, PIC

4.4.2 Map composition

4.5 Data layout transformations

With `pyop3`’s axis trees it is straightforward to construct alternative data layouts for the same data. This is touched upon in section 3.1.1 for the cases of vector and mixed function spaces. Such alternative layouts can be very beneficial for improving the data access patterns of the data, but it presents a new problem: the packing and unpacking code must be different for the different data layouts. Conveniently, using index trees allows us to ignore the problem completely. Since one can think of index trees as being “proto” axis trees, it is possible to index differently laid out data structures using the same index tree and the resulting temporary will have the same shape

```

loop(
    i := dat.axes.index(),
    dat[i].assign(666, eager=False),
)

```

(a) `pyop3` loop expression representing the operation of setting all elements of `dat` to 666. The walrus operator (`:=`) used here is a feature of Python 3.8 and above and is an *assignment expression*. In effect this passes `dat.axes.index()` as an argument to `loop` whilst also binding its value to the variable `i`. The keyword argument `eager=False` is an implementation detail required to enforce that the assignment is a symbolic rather than numeric operation.

```

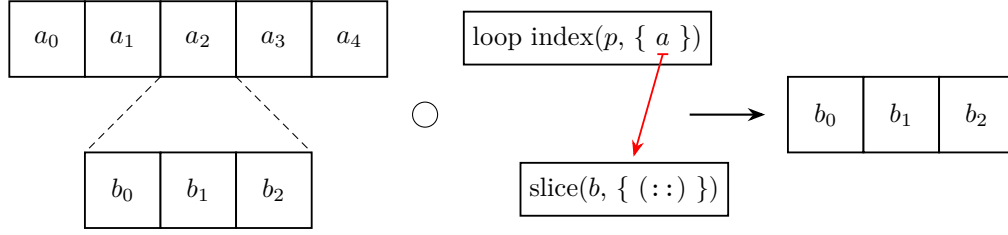
for i in range(len(numpy_dat)):
    numpy_dat[i] = 666

```

(b) Python code equivalent to the loop expression shown in 4.4a where `dat` has been replaced by a numpy array (`numpy_dat`). For simplicity we assume that `numpy_dat` is 1-dimensional.

Figure 4.4: A comparison of a simple assignment loop written in `pyop3` and numpy/Python.

as prescribed by the index tree.

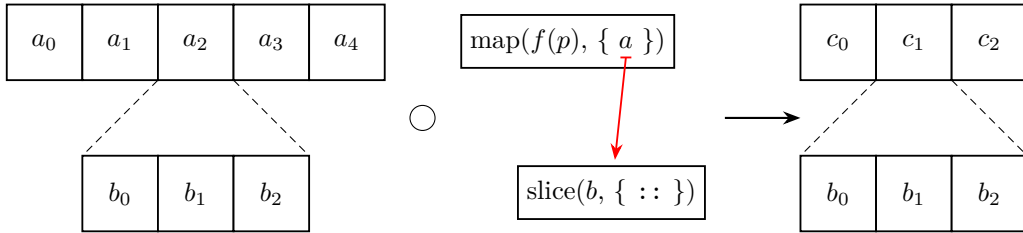


(a) The data layout transformation from the unindexed axis tree (left) to the indexed one (right). Note how the a axis is no longer present in the final axis tree as it has been fully indexed.

Source path	Target path	Target expressions
$\{b\}$	$\{a, b\}$	$\{i_a: i_a^p, i_b: i_b\}$

(b) The indexing information carried by the indexed axis tree (right). Note how the target expression for axis a is the *loop index* i_a^p . This means that the indexed axis tree cannot be interpreted without the outer loop p being present.

Figure 4.5: Index transformation equivalent to indexing a numpy array with shape $(5, 3)$ with indices $[p, :]$, where p is an index coming from some outer loop. The resulting array has shape $(3,)$ because the outermost loop has been fully indexed by p .

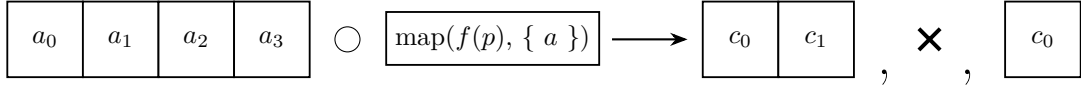


(a) The data layout transformation from the unindexed axis tree (left) to the indexed one (right). Note how the a axis has been replaced by the map axis c .

Source path	Target path	Target expressions
$\{c, b\}$	$\{a, b\}$	$\{i_a: f(i_a^p, i_c), i_b: i_b\}$

(b) The indexing information carried by the indexed axis tree (right). Using a map means that the index for axis a is an expression containing both the outer loop index (i_a^p) and an index over the shape coming from the map's arity (i_c).

Figure 4.6: Index transformation representing the packing of an axis tree with shape $(5, 3)$ containing the entries referenced by the map $f(p)$, where p is some outer loop index. The map has arity 3, so the resulting array has shape $(3, 3)$.

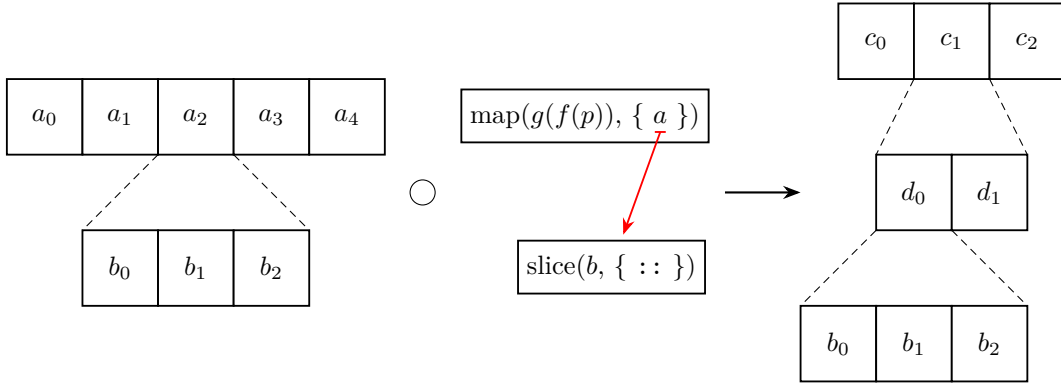


(a) TODO

Source path	Target path	Target expressions
-------------	-------------	--------------------

(b) TODO

Figure 4.7: TODO

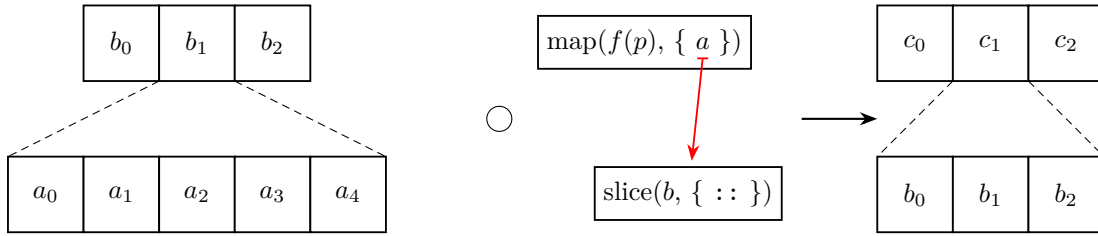


(a) TODO

Source path	Target path	Target expressions
$\{c, d, b\}$	$\{a, b\}$	$\{i_a: g(f(i_a^p, i_c), i_d), i_b: i_b\}$

(b) TODO

Figure 4.8: TODO



(a) The data layout transformation from the unindexed axis tree (left) to the indexed one (right). TODO

Source path	Target path	Target expressions
$\{c, b\}$	$\{a, b\}$	$\{i_a: f(i_a^p, i_c), i_b: i_b\}$

(b) The indexing information carried by the indexed axis tree (right). Note how the values here are entirely identical to those in fig. 4.6b. This is because the indexing operations are kept separate from any layout considerations.

Figure 4.9: Index transformation equivalent to fig. 4.6a apart from the fact that the data layout of the original axis tree has been transposed with axes a and b flipped. Despite this, the indexing transformation and resultant indexed tree are exactly the same as they were before.

Chapter 5

The execution model

Thus far we have established a new abstraction for mesh-like data structures, and an approach for symbolically representing smaller “packed” parts of them. In order for **pyop3** to be a usable library, rather than just an interesting abstraction to consider, three problems remain:

- How are the actual data structures stored in memory?
- How does one express operations to be executed?
- How are these operations executed?

These questions will be answered in this chapter, giving us a fully capable, serial-only, **pyop3** library.

5.1 Data structures

Thus far we have only discussed the *specification* of how data is stored in **pyop3** and not the actual implementation. For continuum mechanics problems one typically needs to have representations for scalars, vectors and matrices. In **pyop3**, recycling the terminology from PyOP2, we call scalars **Globals**, vectors **Dats** and matrices **Mats**. All of these data structures work in parallel, and their parallel implementation is deferred to chapter 6.

5.1.1 Scalars (**Globals**)

Globals are the simplest of **pyop3**’s data structures. They wrap a single scalar value, which may be of any data type (e.g. **int32**, **float64**, **complex128**) and thus have a trivial data layout, hence they have no need for axis trees. It is not valid to index into a **Global** (??).

5.1.2 Vectors (**Dats**)

Thus far, all of the data structures that we have encountered would be stored as **Dats**. **Dats** are constructed with a single axis tree that provides the information necessary to address the underlying flat array that carries the data. Having a single axis tree, **Dats** may be indexed using a single index (??).

Currently **Dats** use numpy arrays as the underlying data storage mechanism, but we intend to permit further array types to enable targeting accelerator architectures like CUDA GPUs (see section 8.2).

5.1.3 Matrices (**Mats**)

Mats require 2 axis trees: one for the rows of the matrix and one for the columns. They rely on PETSc **Mat** objects for the underlying data storage. To improve performance one should preallocate the matrix by constructing a **Sparsity** object and doing a simulated run of all the loop expressions so that non-zeros are put in the right places.

Since **Mats** have two axis trees, two indices are needed when indexing.

5.2 The domain-specific language

5.2.1 Loop expressions

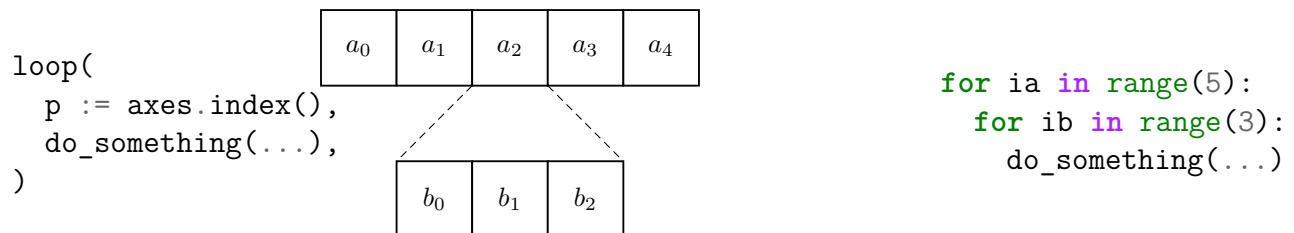


Figure 5.1: A simple example of generating code from a loop expression. The loop expression (left) loops over axis tree **axes** and performs some computation (**do_something**) for each point in the iteration. **axes** is defined to be a two-dimensional linear axis tree with shape (5, 3) and axis labels *a* and *b* (middle). Pseudocode for the code that is generated from this expression is shown to the right. Loop indices *ia* and *ib* correspond to looping over axes *a* and *b* respectively.

Context-sensitive loops

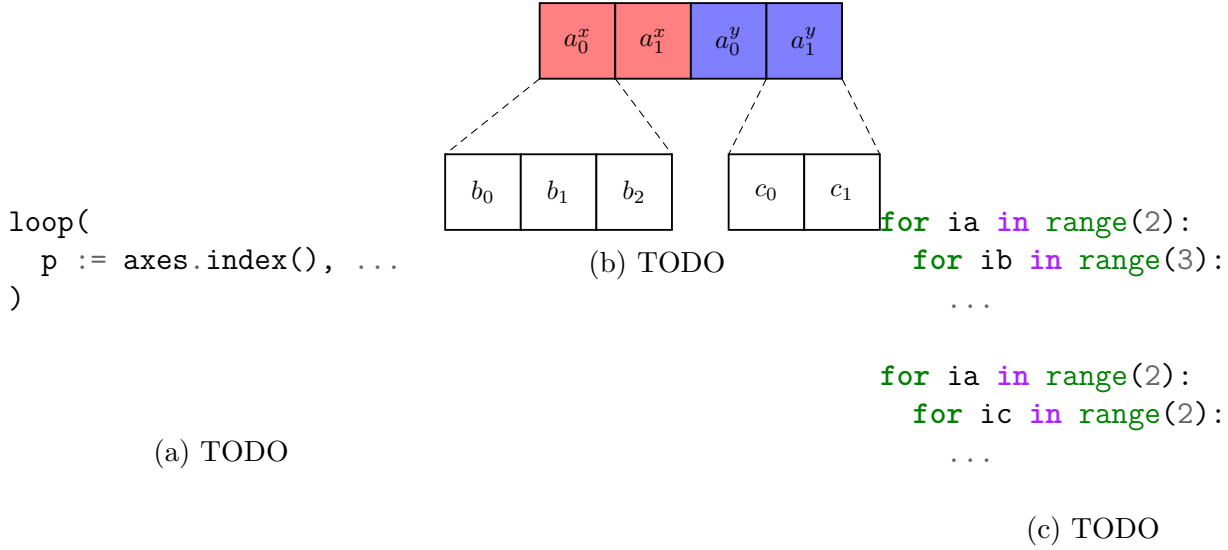


Figure 5.2: TODO

5.2.2 Kernels

5.3 Code generation

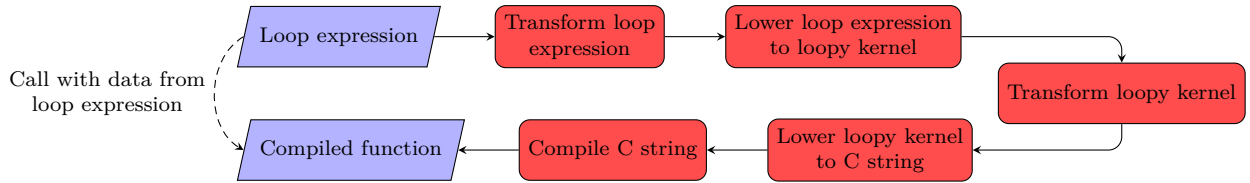


Figure 5.3: The code generation pipeline for the compilation of a loop expression into a callable function. The input (“Loop expression”) and output (“Compiled function”) are shown in blue whilst the intermediate processes are red. The dashed line from input expression to output function is included to represent the fact that the compiled function additionally requires data from the input loop expression in order to be usable.

To aid with the explanation, we will take a straightforward loop expression typical of finite element style codes and demonstrate the transformation and lowering stages of the compilation pipeline as they apply to it:

```

loop(
  p := a.index(),
  kernel(dat0[map0(p), :], dat1[p]),
)

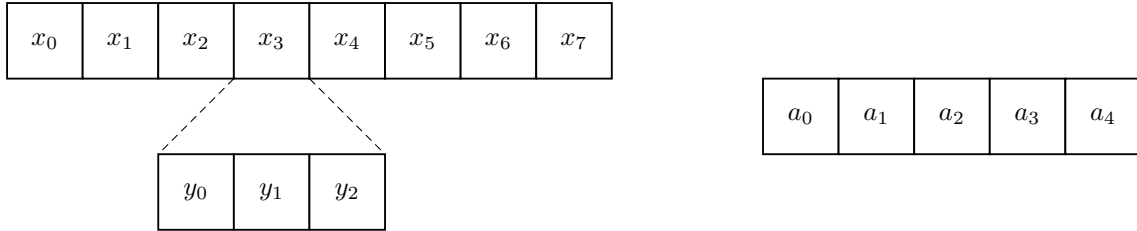
```

In this loop expression a number of terms require further explanation. Firstly, `dat0` and `dat1` are defined to be arrays with shape `(8, 3)` and `(5,)` respectively, with their axis trees appearing

Intent	Pack instruction	Unpack instruction
READ	<code>write(temporary, indexed)</code>	–
WRITE	–	<code>write(indexed, temporary)</code>
RW	<code>write(temporary, indexed)</code>	<code>write(indexed, temporary)</code>
INC	<code>write(temporary, 0)</code>	<code>inc(indexed, temporary)</code>
MIN_WRITE	–	<code>min(indexed, temporary)</code>
MIN_INC	<code>write(temporary, 0)</code>	<code>min(indexed, temporary)</code>
MAX_WRITE	–	<code>max(indexed, temporary)</code>
MAX_INC	<code>write(temporary, 0)</code>	<code>max(indexed, temporary)</code>

Table 5.1: Intent values supported by `pyop3` kernels and their corresponding pack/unpack instructions. In the instructions, the variable “`indexed`” is used to represent the indexed view of some piece of global data (e.g. `dat0[map0(p)]`) and the variable “`temporary`” is the temporary buffer for storing the materialised data. Table entries marked with a “–” indicate that no pack/unpack instruction is emitted for this intent.

as follows:



The axis tree used to construct `dat1` (right) is the same as the one used in the loop index `p := a.index()`. We therefore expect that the generated loop will have the following structure (since axis a has 5 entries):

```
for ia in range(5):
    kernel(...)
```

`dat1` is entirely indexed by the loop index `p`, and so the indexed array `dat1[p]` only has size 1. The situation for `dat0` is more complicated. `map0` is a map from axis a to axis x with arity 2, and the slice notation “`:`” indicates a full slice over the inner axis y . The indexed object `dat0[map0(p), :]` passed through to `kernel` therefore has size 6.

Lastly, the local kernel (`kernel`) is defined to be some function taking two arguments with size 6 and intent `READ`, and size 1 and intent `INC` respectively.

5.3.1 Loop expression transformations

5.3.2 Lowering loop expressions to loopy kernels

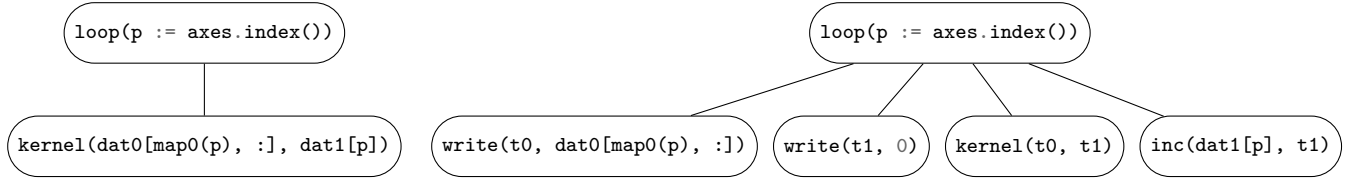


Figure 5.4: The expression tree transformation expanding implicit pack and unpack instructions for the example loop expression (section 5.3). The input loop expression is shown on the left and the output, expanded, loop expression is shown on the right. `kernel` has argument intents of `READ` and `INC` for its first and second argument respectively and so the transformed expression contains `write` and `inc` instructions where appropriate.

KERNEL: pyop3_kernel

ARGUMENTS:

array_0: ArrayArg, type: np:dtype('float64'), shape: unknown in
array_1: ArrayArg, type: np:dtype('int64'), shape: unknown in
array_2: ArrayArg, type: np:dtype('float64'), shape: unknown in/out

DOMAINS:

{ [i_0] : 0 <= i_0 <= 4 }
{ [i_1] : 0 <= i_1 <= 1 }
{ [i_2] : 0 <= i_2 <= 2 }

TEMPORARIES:

t_0: type: np:dtype('float64'), shape: (6), dim_tags: (N0:stride:1)
t_1: type: np:dtype('float64'), shape: (1), dim_tags: (N0:stride:1)

INSTRUCTIONS:

```

for i_0, i_1, i_2
    t_0[i_1*3 + i_2] = array_0[array_1[i_0*2 + i_1]*3 + i_2]
end i_1, i_2
t_1[0] = 0
kernel(t_0, t_1)
array_2[i_0] = array_2[i_0] + t_1[0]
end i_0

```

Figure 5.5: Abbreviated textual representation of the loopy kernel generated for the example expression (section 5.3).

```

void pyop3_kernel(double const *__restrict__ array_0,
                  int64_t const *__restrict__ array_1,
                  double *__restrict__ array_2)
{
    double t_0[6];
    double t_1[1];

    for (int32_t i_0 = 0; i_0 <= 4; ++i_0)
    {
        for (int32_t i_2 = 0; i_2 <= 2; ++i_2)
            for (int32_t i_1 = 0; i_1 <= 1; ++i_1)
            {
                t_0[i_1 * 3 + i_2] = array_0[array_1[2 * i_0 + i_1] * 3 + i_2];
            }
        t_1[0] = 0.0;
        kernel(&(t_0[0]), &(t_1[0]));
        array_2[i_0] = array_2[i_0] + t_1[0];
    }
}

```

Figure 5.6: TODO

5.3.3 Compilation and execution of loopy kernels

Once at the level of a loopy kernel, the rest of the compilation becomes straightforward. Depending on the *target* attribute belonging to a kernel, loopy can generate an appropriate string of C code that pyop3 writes to a file and compiles with a traditional C compiler (e.g. gcc). Once compiled, pyop3 can load the function pointer from the shared object file, allowing it to be executed. This process is unchanged from PyOP2.

For our demo the generated C code can be seen in fig. 5.6. Unsurprisingly it looks very similar to the input loopy kernel (fig. 5.5).

Note Despite being included in the compilation flowchart (fig. 5.3), no transformations are currently applied at the level of the loopy kernel. Transformations at this level would include operations like intra-element vectorisation [13], or enabling the generated code to run on GPUs [7]. These things are considered to be future work (see section 8.2).

Chapter 6

Parallelism

Just like Firedrake (e.g. [2]) and PETSc (e.g. ???), `pyop3` is designed to be run efficiently on even the world’s largest supercomputers. Accordingly, `pyop3` is designed to work SPMD with MPI/distributed memory. As with Firedrake and PETSc, MPI is chosen as the sole parallel abstraction; hybrid models also using shared memory libraries like OpenMP (cite) are not used because the posited performance advantages are contentious [6] and would increase the complexity of the code.

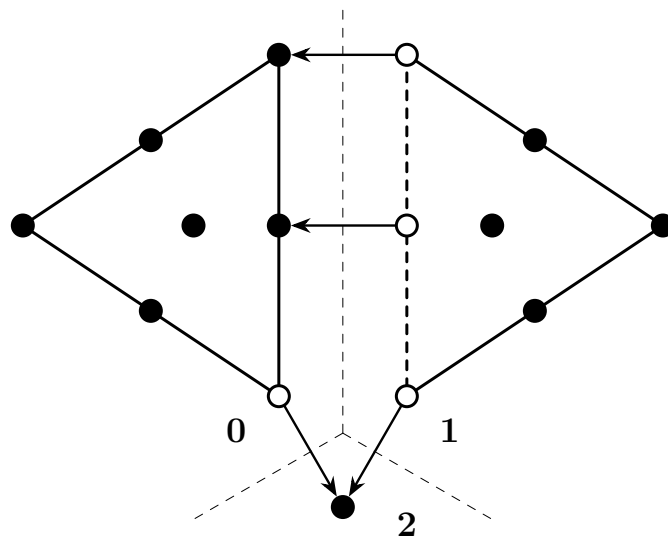
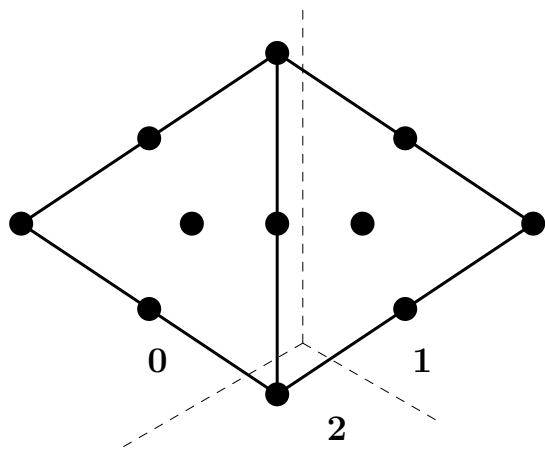
6.1 Message passing with star forests

Almost all message passing in `pyop3` is handled by star forests, specifically by PETSc star forests (`PetscSF`) [14].

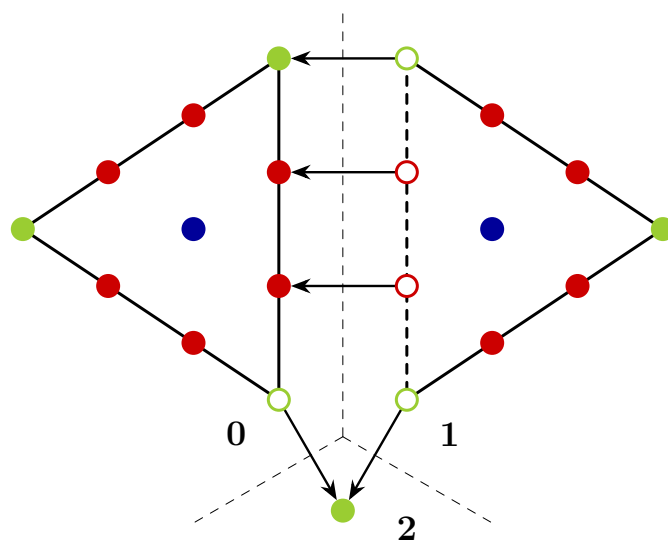
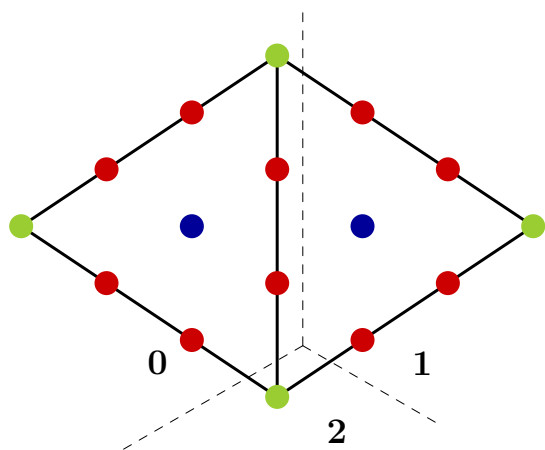
A star forest is defined as a collection of stars, where a star is defined as a tree with a single root and potentially many leaves. Star forests are effective for describing point-to-point MPI operations because they naturally encode the source and destination nodes as roots and leaves of the stars. They can flexibly describe a range of different communication patterns. For example, a value shared globally across n ranks can be represented as a star forest containing a single star with the root node on rank 0 and $n - 1$ leaves, 1 for each other rank. This is shown in Figure ???. Star forests are also suitable for describing the overlap between parts of a distributed mesh. In this case, each star in the forest represents a single point (cell, edge, vertex) in the mesh with the root on the “owning” rank and leaves on the ranks where the point appears as a “ghost”. An example of such a distribution is shown in Figure ??.

Some terminology

- Owned Points are termed “owned” if they are present on a process and are not a leaf pointing to some other rank.



(a) TODO



(b) TODO

Figure 6.1: TODO

- Core Points are “core” if they are owned *and* are not part of (i.e. a root of) any star.

6.2 Overlapping computation and communication

In order to hide the often expensive latencies associated with halo exchanges, `pyop3` uses non-blocking MPI operations to interleave computation and communication. Since distributed meshes only need to communicate data at their boundary, and given the surface-area-to-volume ratio effect, the bulk of the required computation can happen without using any halo data. The algorithm for overlapping computation and communication therefore looks like this:

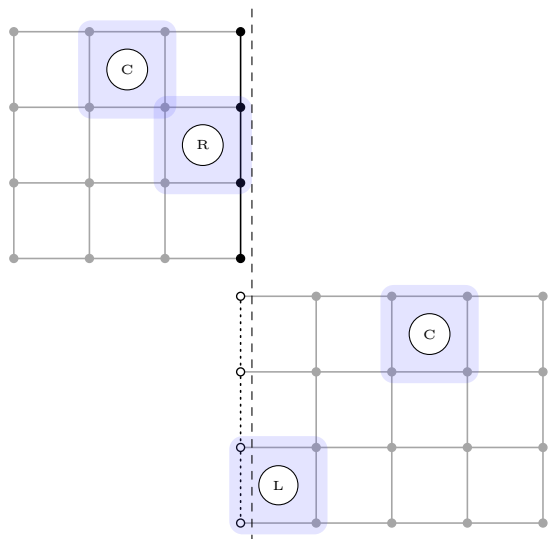
1. Initiate non-blocking halo exchanges.
2. Compute results for data that does not rely on the completion of these halo exchanges.
3. Block until the halo exchanges are complete.
4. Compute results for data that requires up-to-date halo data.

This interleaving approach is used in PyOP2 and has been reimplemented, with slight improvements, in `pyop3`.

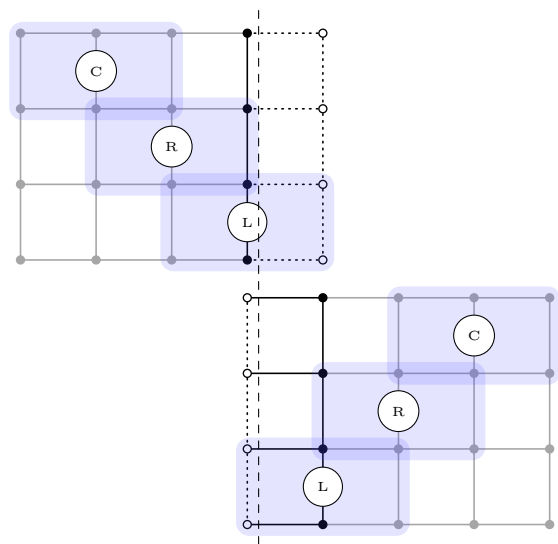
Although this interleaving approach may seem like the most sensible approach to this problem, it is worthwhile to note that there are subtle performance considerations that affect the effectiveness of the algorithm over a simpler blocking halo exchange approach. [3] showed that, in the (structured) finite difference setting, it is in fact often a better choice to use blocking exchanges because (a) the background thread running the non-blocking communication occasionally interrupts the stream of execution, and (b) looping over entries that touch halo data separately adversely affects data locality. With `pyop3` we have only implemented the non-blocking approach for now, though a comparison with blocking exchanges in the context of an unstructured mesh would be interesting to pursue in future.

6.2.1 Lazy communication

Coupled with the goal of “don’t wait for data you don’t need”, `pyop3` also obeys the principle of “don’t send data if you don’t have to”. `pyop3` associates with each parallel data structure two attributes: `leaves_valid` and `pending_reduction`. The former tracks whether or not leaves (ghost points) contain up-to-date values. The latter tracks, in a manner of speaking, the validity of the roots of the star forest. If the leaves of the forest were modified, `pending_reduction` stores the reduction operation that needs to be executed for the roots of the star forest to contain correct



(a) TODO



(b) TODO

Figure 6.2: TODO

values. As an example, were values to be incremented into the leaves¹, a `SUM` reduction would be required for owned values to be synchronised. If there is no pending reduction, the roots are considered to be valid.

The advantage to having these attributes is that they allow `pyop3` to only perform halo exchanges when absolutely necessary. Some pertinent cases include:

- If the array is being written to `op3.WRITE`, all prior writes may be discarded.
- If the array is being read from (`op3.READ`) and all values are already up-to-date, no exchange is necessary.
- If the array is being incremented into (`op3.INC`) multiple times in a row, no exchange is needed as the reductions commute.

One can further extend this by considering the access patterns of the arrays involved. If the iteration does not touch leaves in the star forest then this affects, access descriptor dependent, whether or not certain broadcasts or reduction are required. This is shown, alongside the rest in Algorithm ??.

PyOP2 is able to track leaf validity, but does not have a transparent solution for commuting reductions.

6.3 Performance results

¹For this to be valid the leaves need to be zeroed beforehand.

Chapter 7

Firedrake integration

7.1 Packing

7.1.1 Tensor product cells

7.1.2 Hexahedral elements

Chapter 8

Summary

8.1 Comparison to related work

8.2 Future work

8.3 Conclusions

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