Optimal Finite Element Integration

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1. INTRODUCTION

The need for rapidly implementing high performance, robust, and portable finite element methods has led to approaches based on automated code generation. This has been proved successful in the context of the FEniCS [Logg et al. 2012] and Firedrake [Firedrake contributors 2014] projects, which have become increasingly popular over the last years. In these frameworks, the weak variational form of a problem is expressed at high-level by means of a domain-specific language. The mathematical specification is manipulated and then passed to a form compiler, which generates a representation of local assembly operations. These operations numerically evaluate problem-specific integrals in order to compute so called local matrices and vectors, which represent the contributions from each element in the discretized domain to the equation solution. Local assembly code must be high performance: as the complexity of a variational form increases, in terms of number of derivatives, pre-multiplying functions, and polynomial order of the chosen function spaces, the resulting assembly kernels become more and more computationally expensive, covering a significant fraction of the overall computation run-time.

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Producing high performance implementations is, however, non-trivial. The complexity of mathematical expressions involved in the numerical integration, which varies from problem to problem, and the small size of the loop nest in which such integral is computed obstruct the optimization process. Traditional vendor compilers, such as *GNU's* and *Intel's*, fail at exploiting the structure inherent assembly expressions. Polyhedral-model-based source-to-source compilers, for instance [Bondhugula et al. 2008], mainly apply aggressive loop optimizations, such as tiling, but these are not particularly helpful in our context. This lack of suitable optimizing tools has led to the development of a number of higher-level approaches to maximize the performance of local assembly kernels. In [Olgaard and Wells 2010], it is shown how automated code generation can be leveraged to introduce domain-specific optimizations, which a user cannot be expected to write "by hand". [Kirby et al. 2005] and [Russell and Kelly 2013] have studied, instead, different optimization techniques based on a mathematical reformulation of finite element integration. In [Luporini et al. 2014], we have made one step forward by showing that different forms, on different platforms, require distinct sets of transformations if close-to-peak performance must be reached, and that low-level, domain-aware code transformations are essential to maximize instruction-level parallelism and register locality. The problem of optimizing local assembly routines has been tackled recently also for GPU architectures, for instance in [Knepley and Terrel 2013], [Klöckner et al. 2009], and [Bana et al. 2014].

Our research has resulted in .... we build on our previous work [Luporini et al. 2014] ... and present a ... We argue that for complex, realistic forms, peak performance can be achieved only by ... ... also low-level optimisation ... ...also for the first time we provide a formal explanation of the math in terms of compiler theory - Deficiencies of previous approaches

This is all implemented in COFFEE, which in turn is integrated with the Firedrake framework. We provide an extensive and unprecedented performance evaluation across a number of forms of increasing complexity, including some based on complex (hyperelasticity) models. We characterize our problems by varying polynomial order of the employed function spaces and number of pre-multiplying functions. To clearly distinguish the improvement achieved by this work, we will compare, for each test case, X sets of code variants: 1) unoptimized code, i.e. a local assembly routine as returned from the form compiler; 2) code optimized by FEniCS, i.e. the work in [Olgaard and Wells 2010]; 3) code optimized as described in [Luporini et al. 2014]; ....

2. PRELIMINARIES

We review finite element integration and possible implementations using notation and examples adopted in [Olgaard and Wells 2010] and [Russell and Kelly 2013].

We consider the weak formulation of a linear variational problem

$$\begin{aligned} &Find\ u\ \in U\ such\ that \\ &a(u,v) = L(v), \forall v \in V \end{aligned} \tag{1}$$

where a and L are, respectively, a bilinear and a linear form. The set of *trial* functions U and the set of *test* functions V are discrete function spaces. For simplicity, we assume $U = V$ and $\{\phi_i\}$ be the set of basis functions spanning U. The unknown solution u can be approximated as a linear combination of the basis functions $\{\phi_i\}$. From the solution of the following linear system it is possible to determine a set of coefficients to express u

$$A\mathbf{u} = b \tag{2}$$

in which A and b discretize a and L respectively:

$$\begin{aligned} A_{ij} &= a(\phi_i(x), \phi_j(x)) \\ b_i &= L(\phi_i(x)) \end{aligned} \tag{3}$$

The matrix A and the vector b are computed in the so called assembly phase. Then, in a subsequent phase, the linear system is solved, usually by means of an iterative method, and $\mathbf{u}$ is eventually evaluated.

We focus on the assembly phase, which is often characterized as a two-step procedure: *local* and *global* assembly. Local assembly is the subject of the paper: this is about computing the contributions that an element in the discretized domain provide to the approximated solution of the equation. Global assembly, on the other hand, is the process of suitably "inserting" such contributions in A and b.

Without loss of generality, we illustrate local assembly in a concrete example; that is, the evaluation of the local element matrix for a Laplacian operator. Consider the weighted Laplace equation

$$-\nabla \cdot (w \nabla u) = 0 \tag{4}$$

in which u is unknown, while w is prescribed. The bilinear form associated with the weak variational form of the equation is:

$$a(v, u) = \int_\Omega w \nabla v \cdot \nabla u \, \mathrm{d}x \tag{5}$$

The domain Ω of the equation is partitioned into a set of cells (elements) T such that $\bigcup T = \Omega$ and $\bigcap T = \emptyset$. By defining $\{\phi_i^K\}$ as the set of local basis functions spanning U on the element K, we can express the local element matrix as

$$A_{ij}^K = \int_K w \nabla \phi_i^K \cdot \nabla \phi_j^K \, \mathrm{d}x \tag{6}$$

The local element vector L can be determined in an analogous way.

2.1. Quadrature Mode

Quadrature schemes are conveniently used to numerically evaluate A_{ij}^K. For convenience, a reference element K_0 and an affine mapping $F_K : K_0 \to K$ to any element $K \in T$ are introduced. This implies a change of variables from reference coordinates X_0 to real coordinates $x = F_K(X_0)$ is necessary any time a new element is evaluated. The numerical integration routine based on quadrature representation over an element K can be expressed as follows

$$A_{ij}^K = \sum_{q=1}^{N} \sum_{\alpha_3=1}^{n} \phi_{\alpha_3}(X^q) w_{\alpha_3} \sum_{\alpha_1=1}^{d} \sum_{\alpha_2=1}^{d} \sum_{\beta=1}^{d} \frac{\partial X_{\alpha_1}}{\partial x_\beta} \frac{\partial \phi_i^K(X^q)}{\partial X_{\alpha_1}} \frac{\partial X_{\alpha_2}}{\partial x_\beta} \frac{\partial \phi_j^K(X^q)}{\partial X_{\alpha_2}} det F_K' W^q \tag{7}$$

where N is the number of integration points, W^q the quadrature weight at the integration point X^q, d is the dimension of Ω, n the number of degrees of freedom associated to the local basis functions, and det the determinant of the Jacobian matrix used for the aforementioned change of coordinates.

2.2. Tensor Contraction Mode

Starting from Equation 7, exploiting basic mathematical properties we can rewrite the expression as

$$A_{ij}^K = \sum_{\alpha_1=1}^{d} \sum_{\alpha_2=1}^{d} \sum_{\alpha_3=1}^{n} detF'_K w_{\alpha_3} \sum_{\beta=1}^{d} \frac{X_{\alpha_1}}{\partial x_\beta} \frac{\partial X_{\alpha_2}}{\partial x_\beta} \int_{K_0} \phi_{\alpha_3} \frac{\partial \phi_{i_1}}{\partial X_{\alpha_1}} \frac{\partial \phi_{i_2}}{\partial X_{\alpha_2}} dX. \tag{8}$$

A generalization of this transformation has been proposed in [Kirby and Logg 2007]. By only involving reference element terms, the integral in the equation can be pre-evaluated and stored in a temporary. The evaluation of the local tensor can then be abstracted as

$$A_{ij}^K = \sum_{\alpha} A^0_{i_1 i_2 \alpha} G^\alpha_K \tag{9}$$

in which the pre-evaluated "reference tensor" $A_{i_1 i_2 \alpha}$ and the cell-dependent "geometry tensor" G^α_K are exposed.

2.3. Qualitative Comparison

Depending on the form being considered, the relative performance of the two modes, in terms of number of operations executed, can vary even quite dramatically. The presence of derivatives or coefficient functions in the input form tends to increase the size of the geometry tensor, making the traditional quadrature mode increasingly more indicate for "complex" forms. On the other hand, speed ups from adopting tensor mode can be significant in a wide class of forms in which the geometry tensor remains "sufficiently small".

These two modes have been implemented in the Fenics Form Compiler. In this compiler, a simple heuristic is used to choose the most suitable mode for a given form. It consists of analysing each monomial in the form, counting the number of derivatives and coefficient functions, and checking if this number is greater than a constant found empirically [Logg et al. 2012]. We will later comment on the efficacy of this approach (Section 4. For the moment, we just recall that one of the goals of this research is to produce an intelligent system that is capable of selecting the optimal mode at the monomials level – no heuristics, no "global" choice of the mode for all monomials in the form – without affecting the cost of code generation.

3. OPTIMALITY OF LOOP NESTS

In this section, we characterize our definition of optimality and we describe the assumptions under which it holds.

In order to make the document self-contained, we start by reviewing basic compiler terminology.

Definition 1 (Perfect and imperfect loop nests)**.** *A loop nest is said to be perfect when non-loop statements appear only in the body of the innermost loop. If this condition does not hold, a loop nest is said imperfect.*

A straightforward property of perfect nests is that hoisting invariant expressions from the innermost loop to the preheader (i.e., the block that precedes the entry point of the nest) is a safe transformation. We will make use of this property.

Definition 2 (Linear loop)**.** *A loop L defining the iteration space I through the iteration variable i, or simply L_i, is linear if all expressions appearing in the body of L that use i to access some memory locations are linear functions over I.*

In this work, we are particularly interested in the following class since it naturally arises from the math described in Section 2.

Definition 3 (Perfect multilinear loop nest)**.** *A perfect multilinear loop nest of arity n is a perfect nest composed of n loops, in which all of the expressions appearing in the body of the innermost loop are linear in each loop L_i separately.*

Note that nothing prevents a perfect multilinear loop nest from being rooted in a deeper, possibly imperfect loop nest. In fact, we will later focus on this particular structure. First, we need to define optimality for perfect multilinear loop nests. To this purpose, it is convenient to introduce the notion of sharing.

Definition 4 (Sharing)**.** *A loop L_i presents sharing if it contains at least two expressions depending on i that are symbolically identical.*

Figure 1 shows an example of a trivial multilinear loop nest of arity $n = 2$ with sharing along dimension k.

```
for (j = 0; j < N; j++)
  for (k = 0; k< 0; k++)
    A[j,k] += B[k]*C[j]*b + B[k]*D[j]*c
```

Fig. 1: Multilinear loop nest with sharing

We can now present a simple yet fundamental result.

Proposition 1. *Sharing in a perfect multilinear loop nest $LN = [L_{i_0}, L_{i_1}, ..., L_{i_{n-1}}]$ can always be eliminated.*

Proof. The demonstration is by construction and exploits linearity. We want to transform LN into LN' such that there is no sharing is any $L_i \in LN'$. Starting from the innermost loop $L_{i_{n-1}}$, the expressions are "flattened" by expanding all products involving terms depending on Li_{n-1}. Being on the same level of the expression tree, such terms can then be factorized. Due to linearity, each factored product only has one term depending on $L_{i_{n-1}}$, and such term is now unique in the expression. The other terms, independent of $L_{i_{n-1}}$, are, by definition, loop-invariant, and as such can be hoisted at the level of $L_{i_{n-2}}$. This procedure can be applied recursively up to L_{i_0}: multilinearity allows factorization at each level; perfectness ensures hoisting is always safe. □

Based on this proposition, we define optimality as follows.

Definition 5 (Optimality of a multilinear loop nest)**.** *The synthesis of a multilinear loop nest is optimal if the amount of operations performed in the innermost loop is minimum.*

In other words, optimality implies there is no other synthesis able to further decrease the number of operations in the innermost loop. Note that this definition does not take into account memory requirements. If the loop nest were memory-bound – the ratio of operations to bytes transferred from memory to the CPU being too low – then speaking of "optimality" would clearly make no sense. In the following, we assume to operate in a CPU-bound regime, in which the body of loop nests are characterized by arithmetic-intensive expressions. This suits the context of finite element integration.

A second result follows.

Proposition 2. *An optimal synthesis for a perfect multilinear loop nest LN can deterministically be found.*

Proof. By construction. Loop-dependent terms are logically grouped into n disjoint sets S_i, each S_i containing all terms depending on L_i. These sets are sorted in descending order based on their cardinality. By establishing a one-to-one mapping between set indices and loop indices, we produce a new loop permutation. The loop permutation is semantically correct because of perfectness. In this new order, loops are placed such that as going down the nest, L_i is characterized by less unique terms than L_{i-1}. Starting from $L_{i_{n-1}}$, we can apply the sharing-removal procedure described in Proposition 1. This renders $L_{i_{n-1}}$ optimal. In particular, the number of operations is equal to $LN_{ops} = \#S_{i_{n-1}} + (\#S_{i_{n-1}} - 1)$, in which the second term represents the cost of the summation. □

We now consider generic loop nests in which multilinearity applies to a subset of loops only. Consider the example in Figure 2.

```
for (e = 0; e < L; e++)
  ...
  for (i = 0; i < M; i++)
  ..
    for (j = 0; j < N; j++)
      for (k = 0; k< O; k++)
        A[e,j,k] += F(...)
```

Fig. 2: Loop nest example

The imperfect nest $LN = [L_e, L_i, L_j, L_k]$ comprises a reduction loop L_i and a perfect doubly nested loop $[L_j, L_k]$, which we assume to be multilinear. The right hand side of the statement computing the multidimensional array `A` is a generic expression `F` including standard arithmetic operations such as addition and multiplication. We observe that `F` might contain sub-expressions that depend on a subset of loops only and, as such, hoistable outside of LN as long as data dependencies are preserved (note that LN is imperfect). One could think of searching for sub-expressions independent of L_e, for which the reduction could be pre-evaluated, thus obtaining a decrease proportional to M in the operation count. However, finding or exposing such reducible sub-expressions requires, in general, a full exploration of the expression tree transformation space. This is obviously challenging, and so is the problem of synthesizing an optimal LN' starting from LN. Even though we assumed we could generate LN' in non-exponential time, the following issues should be addressed

— as opposed to what happens with hoisting in perfect multilinear loop nests, the temporary variable size would be proportional to the number of non-reduction loops crossed (in the example, $N \cdot O$ for sub-expressions depending on $[L_i, L_j, L_k]$ and $L \cdot N \cdot O$ for those depending on $[L_e, L_i, L_j, L_k]$). This might shift the loop nest from a CPU-bound to a memory-bound regime, which might be counter-productive for actual runtime;
— the transformations exposing multi-invariant sub-expressions could require expansion and factorization. In terms of number of operations, the save originating from the elimination of the reduction loop could be overwhelmed by the increase in arithmetic complexity of L_k (e.g., expansion can increase the operation count, e.g. $A(B + C) = AB + AC$).

We then refine our definition of optimality for generic loop nests as follows

Definition 6 (Optimality of a loop nest)**.** *The synthesis of a loop nest is optimal if, under a set of memory constraints* C*, the total amount of operations performed in all innermost loops is minimum.*

Note how the definition contemplates the possibility for a nest to have multiple innermost loops. In fact, multiple sub-nests could be rooted in the outermost loop, either because part of the input or result of suitable transformations.

4. SYNTHESIS OF OPTIMAL LOOP NESTS IN FINITE ELEMENT INTEGRATION

In this section, we instantiate Definition 6 in our domain of interest, finite element integration. This will require reasoning at two different levels of abstraction: the math, in terms of the multilinear forms arising from the weak variational formulation of a problem, which we reviewed in Section 2; and the (partly multilinear) loop nests implementing such forms.

Our point of departure is the example loop nest in Figure 2. This loop nest is actually a simplified view of a typical bilinear form implementation. L_e represents iteration over the elements of a mesh; L_i derives from using numerical quadrature; $[L_j, L_k]$ implement the computation over test and trial functions. We deliberately omitted useless portions of code to not hinder readability (e.g. matrix insertion) and to avoid tying our discussion to specific forms (e.g. `F` is unspecified).

From domain knowledge, we make the following observations. 1) $L >>> M, N, O$; that is, the number of elements L is typically order of magnitude larger than both quadrature points (M) and degrees of freedom (N and O for test and trial functions); 2) $[L_j, L_k]$ (or simply L_j with a linear form) is perfect and multilinear; this naturally descends from the translation of Equation 7 into a loop nest.

4.1. Memory constraints

The fact that the iteration space of L_e is so larger than that of other loops suggests we should be cautious when hoisting out of LN. Imagine a time stepping loop L_t wraps LN. One could then think of identifying time-invariant sub-expressions that access both geometry and reference element terms and pre-evaluate them within L_t. Unless adopting complex engineering solutions (e.g. aggressive blocking), which are practically difficult to devise and maintain, this kind of code motion increases the working set by $O(L)$. It is our opinion, therefore, that the drop in number of operations would be overwhelmed, from the run-time viewpoint, by the larger memory pressure.

A second, more general observation is that, for certain forms and discretizations, aggressive hoisting can make the working set exceed the size of "some level of local memory" (e.g. the last level of private cache on a conventional CPU, the shared memory on a GPU). We will provide precise details about this in the following sections. For the moment, and just as one of many possible examples, note that applying tensor contraction mode (see Section 2), which essentially means lifting code outside of L_e, requires a set of temporary arrays of size $N \cdot O$; with some discretizations, this can break the local memory threshold.

Based upon these considerations, we add two constraints to C (see Definition 6)

(1) The size of a temporary due to code motion cannot be bigger than the size of the multilinear loop nest iteration space.
(2) The total size of the hoisted temporaries cannot exceed a threshold T_H

A corollary of $C1$ is that hoisting expressions involving geometry terms outside of L_e becomes forbidden.

4.2. Minimizing the Operation Cost

Definition 6 states that a necessary condition for a loop nest synthesis to be optimal is that the number of operations in all innermost loops is minimum. We now discuss how we can systematically achieve this.

Eliminating sharing from the multilinear loops does not suffice. In fact, we wonder whether, and under what transformations, the reduction imposed by L_i could be pre-evaluated, as already suggested in 6, and the operation count be reduced.

To answer this question, we make use of a result – the foundation of tensor contraction mode – from Kirby and Logg [2007]. Essentially, multilinear forms can be seen as sums of monomials, each monomial being an integral over the equation domain of products (of derivatives) of functions from discrete spaces; such monomials can always be reduced to a product of two tensors (see Section 2). We interpret this result at the loop nest level: with the input as in Figure 2, we can always dissect `F` into distinct sub-expressions (the monomials). Each sub-expression is then factorized so as to split constant from $[L_i, L_j, L_k]$-dependent terms, the latter ones are hoisted outside of LN, and finally pre-evaluated into temporaries. As part of this pre-evaluation, the reduction induced by L_i vanishes. In the following, we simply refer to this special sort of code hoisting as "*pre-evaluation*".

The challenge is to understand when, and for which monomials, pre-evaluation is profitable. We propose an algorithm and a discussion of its optimality.

The intuition of the algorithm for optimal loop nest synthesis is shown in Figure 3.

```
dissect the input expression into monomials
for each monomial M:
  θ_w = estimate ops after pre-evaluation
  θ_wo = estimate ops without pre-evaluation
  if θ_w < θ_wo and memory constraints satisfied:
    mark M as candidate for pre-evaluation
for each monomial M:
  if M does not share terms with M', an unmarked monomial:
    extract M into a separate loop nest
    apply pre-evaluation to M
for each expression:
  remove sharing
```

Fig. 3: Intuition of the main algorithm

The point of departure consists of understanding the impact, as number of operations saved or introduced, of pre-evaluation. This is studied "locally"; that is, for each monomial, in isolation. If we estimate that, for a given monomial, pre-evaluation will decrease the operation count, then the corresponding sub-expression is extracted, a sequence of transformation steps – involving expansion, factorization, code motion – takes place (details in Section 5), and the evaluation eventually performed. The result is a set of n-dimensional tables (these can be seen as "slices" of the reference tensor at the math level), n being the arity of the multilinear form. Identical tables are mapped to the same temporary. Eventually, sharing is removed from the resulting expressions by applying a procedure as described in Proposition 2. The transformed loop nest is as in Figure 4.

Before elaborating on the profitability of pre-evaluation, we need to discuss under which conditions this approach, based on a "local analysis" of monomials, is optimal.

```
for (e = 0; e < L; e++)
  ...
  // Pre-evaluated tables
  ...
  // Loop nests for each dissected monomial
  for (j = 0; j < N; j++)
    for (k = 0; k< O; k++)
      A[e,j,k] += F(...)
    for (k = 0; k< O; k++)
      A[e,j,k] += G(...)
    ...
  // Loop nest for monomials for which run-time
  // integration (/i/ loop) is preferable
  for (i = 0; i < M; i++)
  ..
    for (j = 0; j < N; j++)
      for (k = 0; k< O; k++)
        A[e,j,k] += H(...)
```

Fig. 4: Optimized Loop nest example

Proposition 3. *Consider an expression comprising a set of monomials M. Let P be the set of pre-evaluated monomials, determined as described in Figure 3, and be $Z = M \setminus P$. Assume that:*

(*1*) *the cost function employed is optimal; that is, it predicts correctly whether pre-evaluation is profitable or not for a monomial*
(*2*) *pre-evaluating distinct monomials does not produce identical tables*
(*3*) *monomials in P do not share terms*

Then, the loop nest LN is optimal under memory constraints C, once sharing is removed.

Proof. We first comment on the assumptions. 1) How to create an optimal cost function is discussed in Section 4.3. 2) A pathological case due to symmetries in basis functions, which in practice rarely happens. 3) This could occur in complex forms with several monomials; for simplicity, we ignore this situation (otherwise, a "global" analysis of the monomials would be required).

We distinguish two classes of loop nests rooted in LN: $[L_e, L_j, L_k]$, for the pre-evaluated monomials in P, and $[L_e, L_i, L_j, L_k]$, enclosing the remaining monomials in Z. Since they only differ for the presence of L_i, we relieve notation by omitting all shared loops when discussing operation counts. In particular, we use I to refer to the iteration space size of L_i. The operation count of what we are proving to be the optimal LN synthesis is, therefore, $LN_{ops} = LN_{ops_1} + LN_{ops_2} = \sum_{\alpha}^{\#P} p_\alpha + I \sum_{\beta}^{\#Z} z_\beta$, where p_α and z_β represent the operation cost of monomials in P and Z, respectively.

We start noting that, as explained in Section 4.1, C imposes constraints on hoisting. This narrows the proof to demonstrating the following: A) pre-evaluating any $Z_P : Z_P \subseteq Z$ would increase LN_{ops}; B) not pre-evaluating any $P_Z : P_Z \subseteq P$ would increase LN_{ops}.

A) We prove that $LN'_{ops} = LN'_{ops_1} + LN'_{ops_2} > LN_{ops}$. It is rather obvious that $LN'_{ops_1} \geq LN_{ops_1}$ (it is equal only if, trivially, $Z_P = \emptyset$). We note that if monomials in Z_P share symbols with $\overline{Z} = Z \setminus Z_P$, then we have $LN'_{ops_2} = LN_{ops_2}$, so our statement is true. If, on the other hand, at least one monomial does not share any symbols, we obtain $LN'_{ops_2} < LN_{ops_2}$ or, equivalently, $LN'_{ops_2} = LN_{ops_2} - I \cdot \delta$. What we have to show now is that even by exposing more pre-evaluations, $LN'_{ops_1} \geq LN_{ops_1} + I \cdot \delta$ holds. This is

indeed the case since we rely on assumption 2, which ensures the uniqueness of the pre-evaluated tables (i.e., the absence of sharing) and, therefore, the optimality of LN.

B) In absence of sharing, the statement is trivially true since we would have $LN'_{ops_2} > LN_{ops_2}$, with the cost function being optimal by assumption. Assumption 3 guarantees there can be no sharing within P_Z, which avoids subtle cases wherein pre-evaluation would result sub-optimal due to destroying sharing-removal opportunities. The last case we have to consider is when $p \in P_Z$ shares at least one term with $z \in Z$. This situation cannot actually occur by construction: all candidates for pre-evaluation sharing terms with monomials in Z are "declassed" from P to Z: the rationale is that we would have to pay anyway the presence of the shared terms in the innermost loop due to z, so aggregating p in Z does not increase the operation count. □

4.3. A-Priori Operation Counting

It remains to tie one loose hand: the construction of the pre-evaluation cost function. We introduce the cost function $\theta : M \to \mathbb{N} \times \mathbb{N}$ that, given a monomial, returns two natural numbers representing the optimal operation count without (θ_{wo}) and with (θ_w) pre-evaluation. Since θ is expected to be used by a compiler to drive the transformation process, requirements are simplicity and velocity.

We can easily predict θ_{wo} thanks to our key property, linearity. As described in Proposition 2, a visit of the loop nest suffices to obtain the cost of the optimal synthesis of a multilinear loop nest, namely MLN_{ops}. Then, assuming I to be the size of the L_i iteration space, we simply have that $\theta_{wo} = MLN_{ops} \cdot I$.

For θ_w, things are more complicated. We first need to account for the presence of (derivatives of) coefficients to estimate the *increase factor* ι. This number captures the increase in arithmetic complexity due to the transformations enabling pre-evaluation. To contextualize, consider the example in Figure 5.

```
for (i = 0; i < M; i++)
  for (j = 0; j < N; j++)
    for (k = 0; k< 0; k++)
      A[j][k] += B[j]*B[k]*(f[0]*B[i,0]+f[1]*B[i,1]+f[2]*B[i,2])
```

Fig. 5: Optimized Loop nest example

One can think of this as the (simplified) loop nest originating from the assembly of a pre-multiplied mass matrix. The sub-expression `f[0]*B[i,0]+f[1]*B[i,1]+f[2]*B[i,2]` represents the field f over (tabulated) basis functions B. In order to apply pre-evaluation, the expression needs be transformed to separate f from other (reference element specific) quantities. By expanding the product we observe an increase in the number of L_k-dependent operations of a factor 3 (the local degrees of freedom for the coefficient). ι serves to capture this growth.

With just a single coefficient, ι directly descends from the cost of expansion. In general, however, the calculation is less straightforward. Consider, for example, the case in which multiple coefficients originate from the same function space. Expansion would then lead to identical terms (i.e., identical pre-evaluated tables). Therefore, for a precise estimate of ι, we instead need to calculate the k-combinations with repetitions of n elements, with k being the arity of the multilinear loop nest and n the set of terms involved in the coefficient expansion.

If $\iota \geq I$ we can immediately say that pre-evaluation will not be profitable. This is indeed a necessary condition that, intuitively, tells us that if we add to the innermost

loop more operations than we actually save from eliminating L_i, then for sure $\theta_{wo} < \theta_w$. This observation can speed up the compilation time by decreasing the analysis cost.

If, on the other hand, $\iota < I$, a further step is necessary to estimate θ_w. In particular, we need to calculate the number of reference-element specific terms, ρ, such that $\theta_w = \rho \cdot \iota$. Consider again Figure 5. In the case of the mass matrix, the body of L_k is characterized by just the dot product of test and trial functions, `B[j]*B[k]`, so trivially $\rho = 1$. In general, ρ varies with the discretization and the differential operators employed. For example, in the case of the bi-dimensional Poisson equation, $\rho = 3$. There are several ways of determining ρ. The fastest would be to extract it from high-level analysis of the operators in the form; for convenience, in our implementation we instead project (by analysis of the expression tree) the output of expansion and factorization in the monomial.

5. CODE GENERATION

The analysis described in Section **??** has been fully automated in COFFEE, the optimization system for local assembly used in Firedrake. In this section, we describe the structure of the code generation system and we comment on a set of low-level optimizations.

5.1. Automation through the COFFEE Language

As opposed to what happens in FFC with quadrature and tensor modes, there are no separate trunks in COFFEE handling pre-evaluation, sharing, and code motion in general: all optimizations are expressed as composition of parametric "building-block" operations. This has several advantages. Firstly, extendibility: novel transformations – for instance, sum-factorization in spectral methods – could ideally be expressed using the existing operators, or with small effort building on what is already available. Secondly, generality: other domains sharing properties similar to that of finite element integration (e.g., multilinear loop nests) could be optimized through the same compiler. Thirdly, robustness: the same building-block operations are exploited, and therefore stressed, by different optimization pipelines.

A non-exhaustive list of such operations includes expansion, factorization, re-association, generalized code motion. These are parametric operations. For example, one could ask to factorize only constant or only linear terms, while hoisting can be limited by imposing a constraint on the size of the temporaries. Each of these operations is implemented by suitable manipulation of the abstract syntax tree representing the integration routine.

5.1.1. Heuristic Optimization of Integration-dependent Expressions. As a proof-of-concept of our generality claim,

5.2. Low-level Optimization

...

5.2.1. Avoiding Iteration over Zero-valued Blocks by Symbolic Execution.

5.2.2. Padding and Data Alignment. ...

5.2.3. Vector-promotion of Integration Quantities. ...

6. PERFORMANCE EVALUATION

6.1. Experimental Setup

Experiments were run on a single core of an Intel architecture, a Sandy Bridge I7-2600 CPU, running at 3.4GHz, 32KB L1 cache and 256KB L2 cache. The Intel `icc 14.2` compiler was used. The compilation flags used were `-O3, -xHost, -xAVX, -ip`.

We analyze the run-time performance of four fundamental real problems, which comprise the differential operators that are most common in finite element methods. In particular, our study includes problems based upon the Helmholtz and Poisson equations, as well as elasticity- and hyperelasticity-like forms. The Unified Form Language [Alnæs et al. 2014] specification for these forms, which is the domain specific language that both Firedrake and FEniCS use to express weak variational form, is available at [ufl 2014].

We evaluate the *speed ups* achieved by three sets of optimizations over the original code; that is, the code generated by the FEniCS Form Compiler when no optimizations are applied. In particular, we analyze the impact of the FEniCS Form Compiler's built-in optimizations (henceforth `ffc`), the impact of COFFEE's transformations as presented in [Luporini et al. 2014] (referred to as `fix`, in the following), and the effect of Expression Rewriting and Code Specialization as described in this work (henceforth `auto`, to denote the use of autotuning as described in Section **??**). The `auto` values do not include the autotuner cost, which is commented aside in Section **??**.

The values that we report include the cost of local assembly as well as the cost of matrix insertion. However, the unstructured mesh has been made small enough to fit the L3 cache, so as to minimize the "noise" due to any operations that are not part of the element matrix evaluation itself. However, it has been reiterated over and over (e.g. [Olgaard and Wells 2010]) that as the complexity of a form increseas, the cost of local assembly becomes dominant. All codes were executed in the context of the Firedrake framework.

We vary several aspects of each form, which follows the approach and the notation of [Olgaard and Wells 2010] and [Russell and Kelly 2013]

— The polynomial order of basis functions, $q \in \{1, 2, 3, 4\}$
— The polynomial order of coefficient (or "pre-multiplying") functions, $p \in \{1, 2, 3, 4\}$
— The number of coefficient functions $nf \in \{0, 1, 2, 3\}$

On the other hand, other aspects are fixed

— The space of both basis and coefficient functions is Lagrange
— The mesh is three-dimensional, made of tetrahedrons, for a total of 4374 cells

Figures **??**, **??**, **??**, and **??**, which will be deeply commented in the next section, must be read as "plots, or grids, of plots". Each grid (figure) has two logical axes: p varies along the horizontal axis, while q varies along the vertical axis. The top-left plot in a grid shows speed ups for $[q = 1, p = 1]$; the plot on its right does the same for $[q = 1, p = 2]$, and so on. The diagonal of the grid shows plots for which basis and coefficient functions have same polynomial order, that is $q = p$. Therefore, a grid can be read in many different ways, which allows us to make structured considerations on the effect of the various optimizations.

A plot reports speed-ups over non-optimized FEniCS-Form-Compiler-generated code. There are three groups of bars, each group referring to a particular version of the code (`ffc, fix, auto`). There are four bars per group: the leftmost bar corresponds to the case $nf = 0$, the one on its right to the case $nf = 1$, and so on.

6.2. Performance of Forms

Helmholtz.

Elasticity.

Poisson.

Hyperelasticity.

7. CONCLUSIONS

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