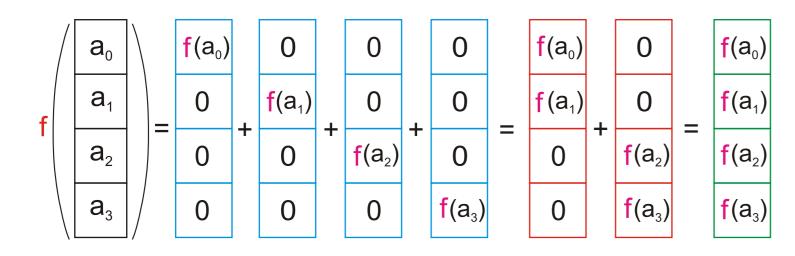
# Reasoning About Sparse Vectors for Loops Code Generation

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# **Motivating example**

Pointwise operator vectorization:



Loop Parellelization:

$$P_{f_j}^n = \sum_{j=0} S_{(j)} \circ A_{f_j} \circ G_{(j)}$$

Sample non-vectorized function processing single FP element.

Pointwise application of 'f' to src, storing results in dst, one at a time. It requires 4 iterations and 4 function calls.

Loop Parellelization: 
$$\mathbf{P}_{f_j}^n = \sum_{j=0}^1 \mathbf{S}_{(j)} \circ A_{f_j} \circ \mathbf{G}_{(j)} \qquad \qquad \mathbf{P}_{f_j}^n = \sum_{j=0}^1 \mathbf{S}_{h_{j,0}} \circ \begin{pmatrix} \mathbf{X} \\ \mathbf{X} \\ k=0 \end{pmatrix} \circ \mathbf{G}_{h_{j,2}}$$

Sample vectorized function processing 2 FP elements at a time.

Pointwise application of 'f' to src, storing results in dst, two at a time. It requires just 2 iterations and 2 function calls.

### The Problem

- Dense vectors are decomposed into iterative sums of sparse vectors.
- Various decompositions (number or vectors and location of non-sparse values) could represent a variety of memory access patterns.
- This allows applying a variety of algebraic transformations to reshape a computation to optimize for vectorization, parallelization, sequential memory access.
- However in such iterative sum, the addition has a special semantics:
  - Mathematically, the sparse values could be treated as zeroes.
  - Operationally, combining sparse and non-sparse value could be seen as an assignment.
- The expressions produced are naturally mapped to SSA form only if certain constraints on structure of sparse vectors under iterative sums are maintained.
- Tracking and enforcing such constraints for correctness proofs is difficult, as they are not adequately enforced by mathematica abstraction used.
- In this work we present a working approach for structural constraints tracking and propagation used in Coq proofs of correctness.

# **Approach**

#### Sparsity Requirements

- 1. Distinguish empty and assigned cells.
- 2. Treat empty cells as some "default" value. Such default value could depend on the context (e.g. 0 for addition but 1 for multiplication).
- 3. In case of "a loop as sparse vector sum" we should never attempt to combine two non-sparse elements. This type of error we will call a "collision".
- 4. Sparsity tracking should be easy to perform during computations.
- 5. Collisions should be seamlessly tracked and propagated across the computation.
- 6. The collision and sparsity tracking should be proof-friendly (easy to deal with in Coq)
- 7. Separate sparsity tracking from actual operations on values as they represent two different aspects of computation.

#### State and Collision Tracking Monad

**Record** Rflags: Type:= mkRFlags (is\_struct: bool; is\_collision: bool). **Definition** rFlagsZero := mkRFlags true false.

**Definition** mappend (a b: Rflags): Rflags :=

mkRFlags

(is\_struct a && is\_struct b)

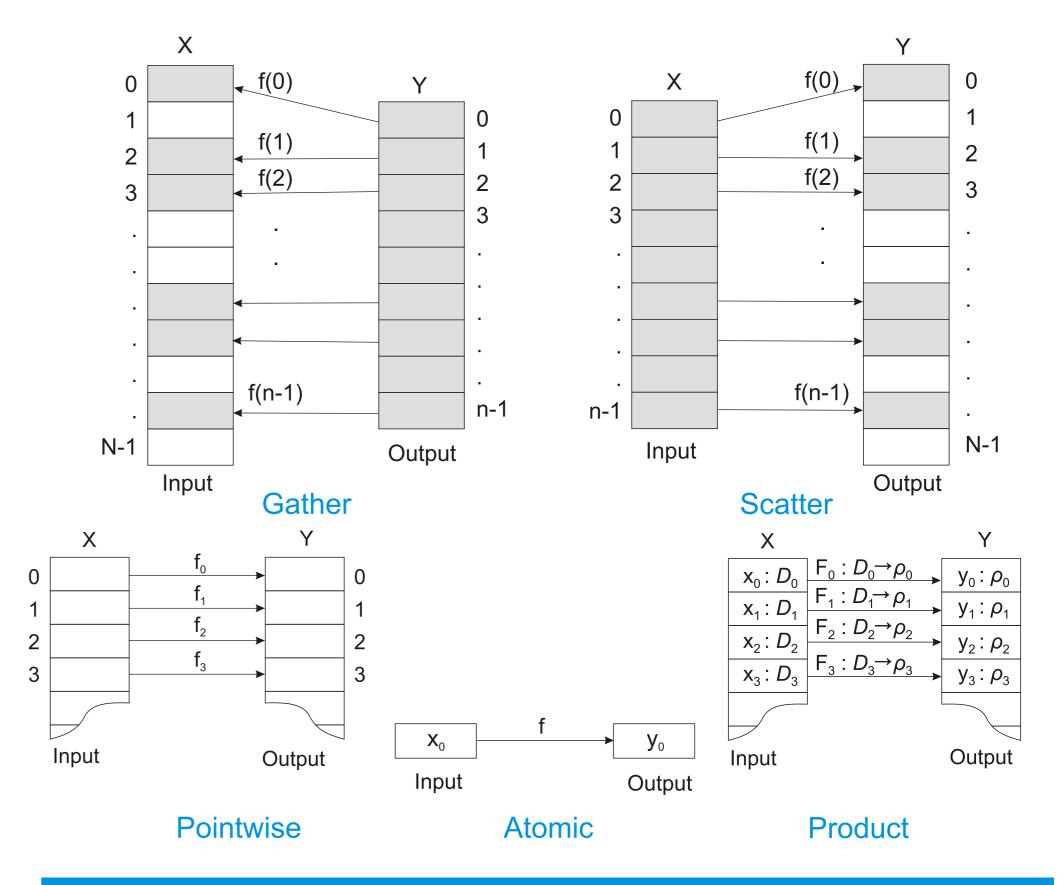
(is\_collision a II (is\_collision b II

(negb (is\_struct a II is\_struct b)))).

**Definition** RMonoid : Monoid Rflags := Build\_Monoid mappend rFlagsZero.

**Definition**  $R_{\theta}$  := writer Rmonoid  $\mathbb{R}$ .

## **Operators**



## **Implementation**

#### "Diamond" Abstraction

Scalar  $\diamond:\ \mathcal{A}
ightarrow\mathcal{A}
ightarrow\mathcal{A}$  $\vec{\diamond}: \mathcal{A}^n \to \mathcal{A}^n \to \mathcal{A}^n$ Vector  $((a_0, a_1, \ldots, a_{n-1}), (b_0, b_1, \ldots, b_{n-1})) \mapsto$  $(a_0 \diamond b_0, a_1 \diamond b_1, \ldots, a_{n-1} \diamond b_{n-1})$ 

 $\diamondsuit: (\mathcal{A}^n \to \mathcal{A}^m) \to (\mathcal{A}^n \to \mathcal{A}^m) \to (\mathcal{A}^n \to \mathcal{A}^m)$ Operation  $(F,G)\mapsto (\mathbf{x}\mapsto F(\mathbf{x})\,\vec{\diamond}\,G(\mathbf{x}))$ 

 $\bigotimes_{i=0}^{n-1} F_i: \mathcal{A}^n \to \mathcal{A}^n$ Iterative  $\mathbf{x} \mapsto \begin{cases} \mathbf{0}^n & \text{if } n = 0, \\ \left( F_{n-1} \, \mathring{\diamond} \left( igotimes_{j=0}^{n-2} F_j \right) \right) (\mathbf{x}) & \text{otherwise} \end{cases}$ 

#### Iterative Sum with Sparsity and Collision Tracking

Let us apply the diamond abstraction demonstrated to  $R_{\theta}$  type (which represents  $\mathbb{R}$  with  $R_{flags}$  state) and summation operator. To do so we specalize previous notation as follows:

> Definition  $\mathcal{A} := \mathcal{R}_{\theta}$ . Definition  $\diamond := liftM2 (+)$ . Definition  $\vec{\diamond} := \text{vector.map2} \diamond$ . Definition  $\delta f g := \lambda x \Rightarrow (f x) \vec{\delta} (g x)$ . Definition  $\mathbf{0}^n := \text{vector.const (ret 0) } \mathbf{n}$ .

This gives us a sparse, collision-tracking PointWise:

Pointwise<sub>n,f</sub> = 
$$\bigotimes_{j=0}^{n-1} \left( S_{(j)_n} \circ A_{f_j} \circ G_{(j)_n} \right)$$

# Summary

- 1. Implementation in Coq proof assistant.
- 2. Each value is tagged with two boolean flags: is struct and is collision.
- 3. Flags structure along with combining operation forms a Monoid.
- 4. Two Monoid instances are used: with and without collision tracking.
- 5. Flags are tracked using Writer Monad.
- 6. Operations on values can not directly examine sparsity flags and thus can not depend on them.
- 7. Sparsity is automatically tracked by the monad. No implicit flags handling in operators implementation.
- 8. Collision is automatically tracked and propagated by the monad.

## **Contact info**

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