Westfälische Wilhelms-Universität Münster

Student Research Competition

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Microsoft

md_poly: A Performance-Portable Polyhedral Compiler based on Multi-Dimensional Homomorphisms

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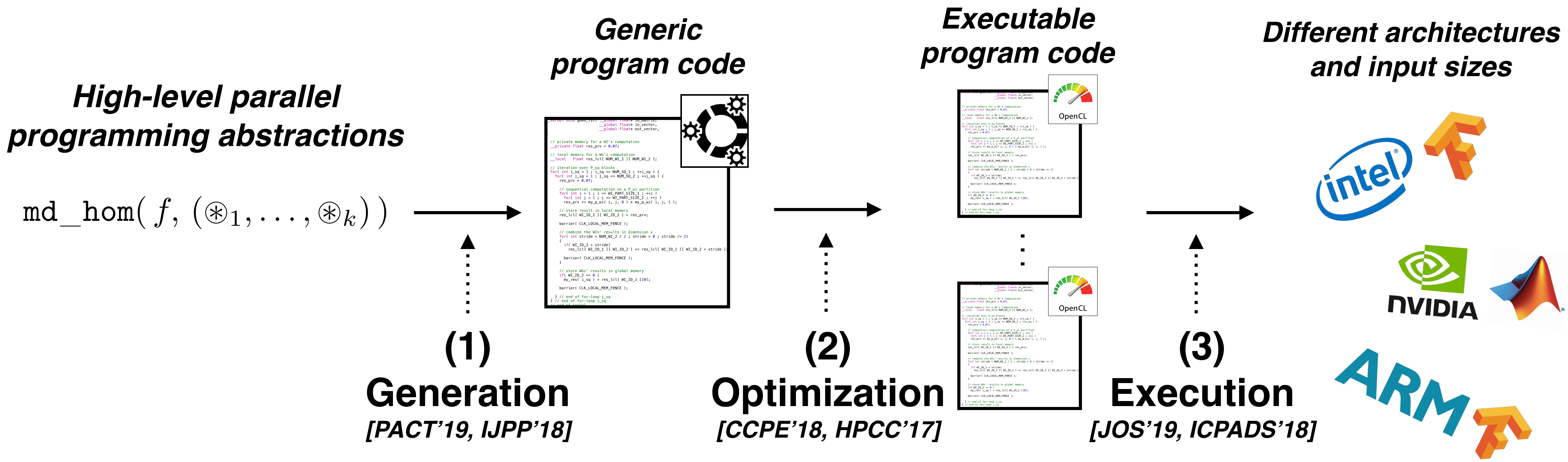
Our Background

We are the developers of the MDH code generation approach:



- **Multi-Dimensional Homomorphisms (MDHs)** are a **formally defined** class of functions that **cover important data-parallel computations**, e.g.: linear algebra routines (BLAS), stencils computations, …
- We enable **conveniently** implementing MDHs by providing a **high-level DSL** for them.
- We provide a **DSL compiler** that **automatically generates OpenCL code** — the standard for uniformly programming different parallel architectures (e.g., CPU and GPU).
- Our OpenCL code is **fully automatically optimizable** (auto-tunable) — for each combination of a **target architecture**, and **input size** — by being generated as targeted to **OpenCL's abstract device models** and as **parametrized in these models' performance-critical parameters.**

Experimental Results

Stencils

CPU	Gaussian (2D)		Jacobi (3D)	
	RW	PC	RW	PC
Lift [2]	4.90	5.96	1.94	2.49
MKL-DNN	6.99	14.31	N/A	N/A

GPU	Gaussian (2D)		Jacobi (3D)	
	RW	PC	RW	PC
Lift [2]	2.33	1.09	1.14	1.02
cuDNN	3.78	19.11	N/A	N/A

[2] Hagedorn et. al, "High Performance Stencil Code Generation with LIFT.", **CGO'18 (Best Paper Award)**.

Data Mining

CPU	Probabilistic Record Linkage					
	2^{15}	2^{16}	2^{17}	2^{18}	2^{19}	2^{20}
EKR [5]	1.87	2.06	4.98	13.86	28.34	39.36

[5] Forchhammer et al. "Duplicate Detection on GPUs.", **HFSL'13**.

Our MDH approach achieves often better performance than well-performing competitors [1]

[1] Rasch, Schulze, Gorlatch. "Generating Portable High-Performance Code via Multi-Dimensional Homomorphisms.", PACT'19

Linear Algebra

CPU	GEMM		GEMV	
	RW	PC	RW	PC
Lift [1]	fails	3.04	1.51	1.99
MKL	4.22	0.74	1.05	0.87

GPU	GEMM		GEMV	
	RW	PC	RW	PC
Lift [1]	4.33	1.17	3.52	2.98
cuBLAS	2.91	0.83	1.03	1.00

Tensor Contractions

GPU	Tensor Contractions								
	RW 1	RW 2	RW 3	RW 4	RW 5	RW 6	RW 7	RW 8	RW 9
COGENT [3]	1.26	1.16	2.12	1.24	1.18	1.36	1.48	1.44	1.85
F-TC [4]	1.19	2.00	1.43	2.89	1.35	1.54	1.25	2.02	1.49

[3] Kim et. al. "A Code Generator for High-Performance Tensor Contractions on GPUs.", **CGO'19**.

[4] Vasilache et al. "The Next 700 Accelerated Layers: From Mathematical Expressions of Network Computation Graphs to Accelerated GPU Kernels, Automatically.", ***TACO,* 2019**.

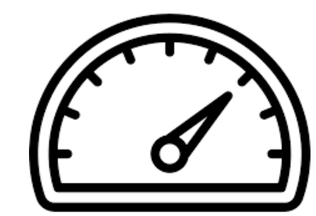
[1] Steuwer et. al, "Lift: A Functional Data-Parallel IR for High-Performance GPU Code Generation", **CGO'17**.

Observation

Comparison: ***MDH Approach*** vs. ***Polyhedral Approaches* (e.g. PPCG)**

- ***Polyhedral approaches*** often provide better *productivity* → automatically parallelize sequential program code (rather than relying on a DSL).

- ***The MDH approach*** achieves often higher *performance* than polyhedral compilers; its generated code is *portable* over different architectures (e.g., GPU and CPU).

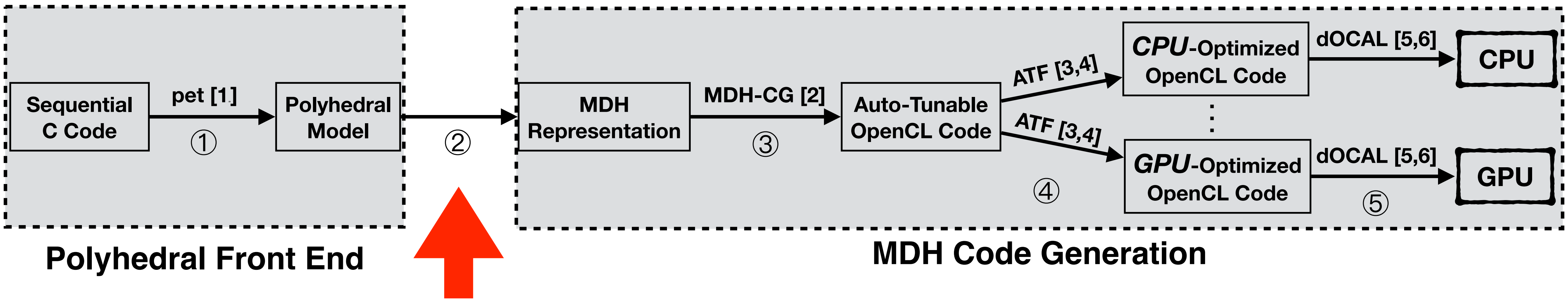


Goal of this work:

Combining the advantages of both approaches

Idea

Using a polyhedral front end for the MDH code generator:



1. Transforming sequential C program to polyhedral model via PET.
2. **Transforming polyhedral model to MDH representation.**
3. Generating auto-tunable OpenCL code from MDH representation.
4. Auto-tuning OpenCL code for particular device and problem size.
5. Executing auto-tuned OpenCL code.

[1] Verdoolaege, Grosser, "Polyhedral Extraction Tool.", IMPACT'12
[2] Rasch, Schulze, Gorlatch, "Generating Portable High-Performance Code via Multi-Dimensional Homomorphisms.", PACT'19
[3] Rasch, Haidl, Gorlatch, "ATF: A Generic Auto-Tuning Framework.", HPCC'17
[4] Rasch, Gorlatch, "ATF: A Generic, Directive-Based Auto-Tuning Framework.", CCPE'19
[5] Rasch, Wrodarczyk, Schulze, Gorlatch, "OCAL: An Abstraction for Host-Code Programming with OpenCL and CUDA.", *ICPADS'18*
[6] Rasch, Bigge, Wrodarczyk, Schulze, Gorlatch. "dOCAL: high-level distributed programming with OpenCL and CUDA.", JOS'19

The MDH DSL

<u>Example:</u> *Matrix Multiplication*

```
MatMul = md_hom( *, (++, ++, +) ) o view( A,B )( i,j,k )( A[i,k], B[k,j] )
```

```
for( int i = 0; i < M ; ++i )
  for( int j = 0; i < N ; ++j )
    for( int k = 0; i < K ; ++k )
      C[i][j] += A[i][k] * B[k][j];
```

MatMul in C

<u>What's happening?</u>

1. Prepare the domain-specific input uniformly for `md_hom`; for this, our DSL provides pattern `view`.
    - <u>here:</u> fuse matrices A and B to 3-dimensional array of pairs consisting of the elements in A and B to multiply: `i,j,k ↦ (A[i,k],B[k,j])`.
2. Apply multiplication (denoted as `*`) to each pair.
3. Combine results in dimension `k` by addition (`+`).
4. Combine results in dimensions `i` and `j` by concatenation (`++`).

Transformation

Polyhedral Model → MDH Representation:

Polyhedral Model is a "structured" representation of the sequential code

```
for( int i = 0; i < M ; ++i )
  for( int j = 0; i < N ; ++j )
    for( int k = 0; i < K ; ++k )
      C[i][j] += A[i][k] * B[k][j];
```

MatMul in C

```
MatMul = md_hom( *, (     ++, +) ) o view( A,B )( i,j,k )( A[i,k], B[k,j] )
```

***isl* [1]**

```
md_hom( f, (++,++,?) )
```

<u>means:</u> *Unknown Combine Operator (UCO)*
→ NO parallelization, BUT tiling, caching, …

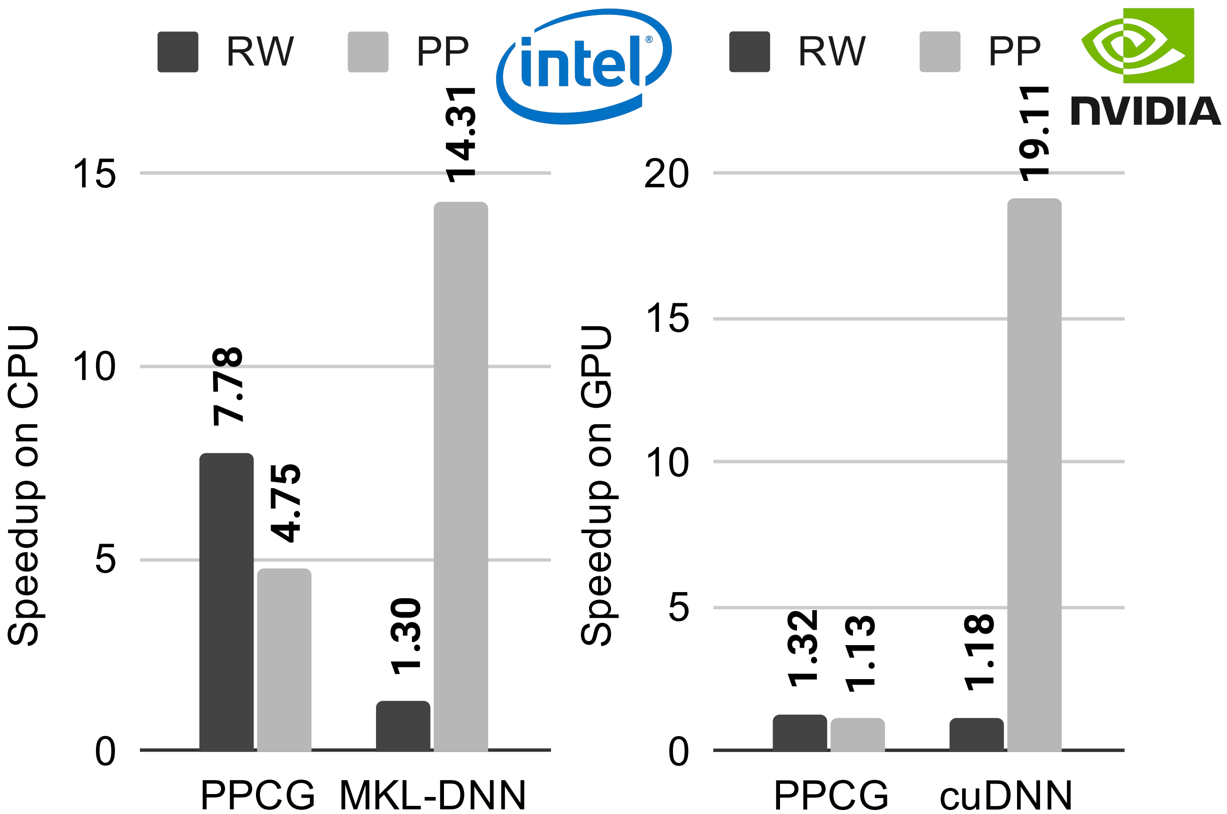
```
T f( T A_i_k, T B_k_j, T C_i_j )
{
  C_i_j += A_i_k * B_k_j;

  return C_i_j;
}
```

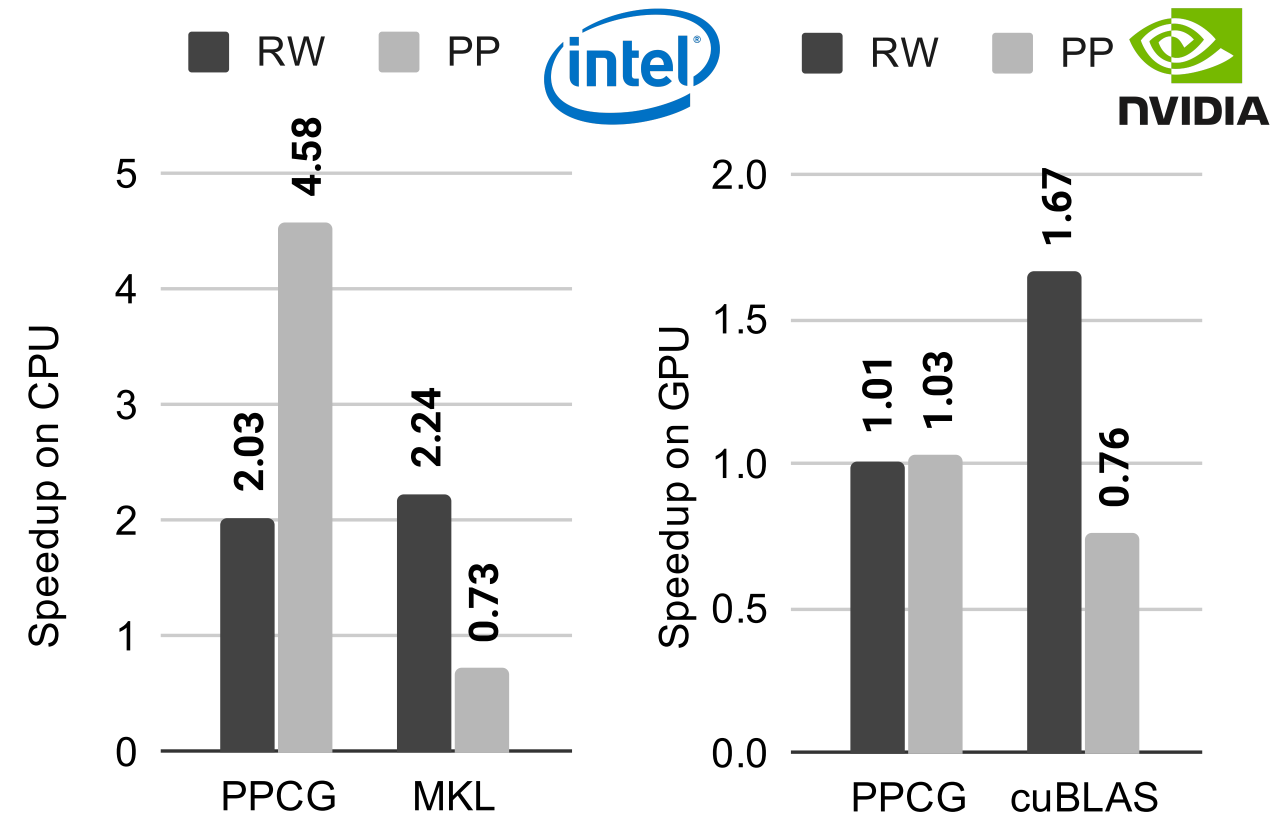
- Variables with `read` or `read-write` access are set as arguments of `f`.
- Variables with `write` access are declared and zero initialized in `f`.
- Variables with `write` or `read-write` access are returned by `f`.

[1] Verdoolaege, "isl: An Integer Set Library for the Polyhedral Model", *ICMS'10*

Experimental Results



Gaussian Convolution



Matrix Multiplication

Hardware
- CPU: Intel Xeon E5
- GPU: NVIDIA V100

Gaussian Convolution
- RW: 1×512×7×7×512
- PP: 1x1x4096x4096x1

Matrix Multiplication
- RW: M,N,K = 10,500,64
- PP: M,N,K = 1024

- **Compared to PPCG:**
  - Competitive performance on GPU: 1.01x – 1.32x
  - Better performance on CPU: 2.03x – 7.78x
- **Compared to Intel MKL/MKL-DNN & NVIDIA cuBLAS/cuDNN:**
  - Competitive and sometimes better performance: 0.73x – 2.24x (19.11x)

Conclusion

We present `md_poly`:

- `md_poly` is based on both the polyhedral model and the MDH code generation approach;
- `md_poly` combines productivity (as in polyhedral compilers) and portable high performance (as in the MDH approach);
- `md_poly` achieves sometimes better performance than hand-optimized approaches.

Future Work:

Evaluating `md_poly` for all applications in PolyBench.

Complicated Combine Operator

PRL = md_hom(weight, (++, $\otimes_{max}$)) o view(…)

```
for (int i = 0; i < NUM_NEW_RECORDS; ++i) {
    match_id[i] = 0;
    match_weight[i] = 0;
    id_measure[i] = 0;
    for (int j = 0; j < NUM_EXISTING_RECORDS; ++j)
{
        // calculate weight
        double weight = calc_weight(...);
        // calculate identity measure
        int id_measure = calc_id_measure(...);
        // store result
        if ((weight >= 15.0 || id_measure == 14) &&
(weight > *match_weight_res)) {
            match_id[i] = i_id[j];
            match_weight[i] = weight;
            id_measure[i] = id_measure;
        }
    }
}
```

Automatically extractable?

Rasch, Schulze, Gorus, Hiller, Bartholomäus, Gorlatch. "High-Performance Probabilistic Record Linkage via Multi-Dimensional Homomorphisms.", SAC'19