

# On Demand Parametric Array Dataflow Analysis

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# Outline

- 1 Motivation
  - General Motivation
  - Our Motivation
- 2 Array Dataflow Analysis
  - Standard
  - Fuzzy
  - On Demand Parametric
- 3 Dynamic Conditions
- 4 Parametrization
  - Overview
  - Representation
  - Introduction
  - Additional Constraints
- 5 Related Work
- 6 Experimental Results
- 7 Conclusion

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# Motivation

- Dataflow analysis determines for read access in a statement instance, the statement instance that wrote the value being read
- Many uses in polyhedral analysis/compilation
  - ▶ array expansion
  - ▶ scheduling
  - ▶ equivalence checking
  - ▶ optimizing computation/communication overlap in MPI programs
  - ▶ derivation of process networks
  - ▶ ...
- Standard dataflow analysis (Feautrier) requires static affine input programs
- Extensions are needed for programs with dynamic/non-affine constructs

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  - ▶ **derivation of process networks**
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- Standard dataflow analysis (Feautrier) requires static affine input programs
- Extensions are needed for programs with dynamic/non-affine constructs

# Our Motivation: Derivation of Process Networks

- Main purpose: extract task level parallelism from dataflow graph

statement      →    process  
flow dependence    →    communication channel

⇒ requires dataflow analysis

- Processes are mapped to parallel hardware (e.g., FPGA)

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⇒ requires dataflow analysis

- Processes are mapped to parallel hardware (e.g., FPGA)

Example:

```
for (i = 0; i < n; ++i) {  
    a = f();  
    g(a);  
}
```



# Dynamic Process Networks

```
int state = 0;
for (i = 0; i <= 10; i++) {
    sample = radioFrontend();
    if (state == 0) {
        state = detect(sample);
    } else {
        state = decode(sample, &value0);
        value1 = processSample0(value0);
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    }
}
```

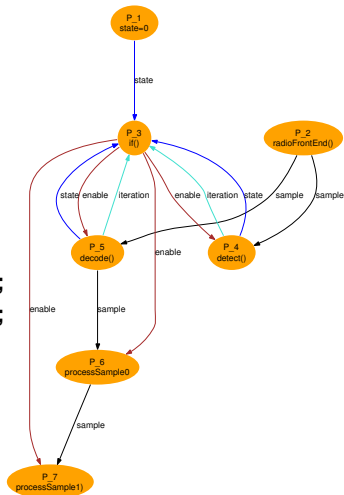


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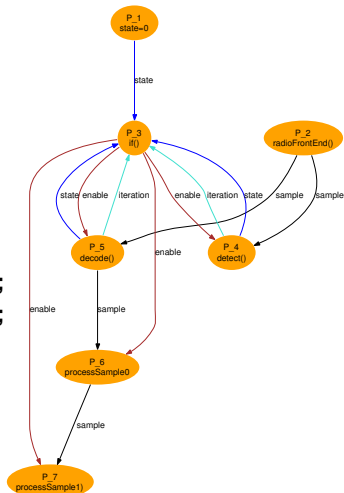
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```

- additional control channels
- determine operation of data channels
- dataflow analysis needs to remain exact, but may depend on run-time information



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## Standard Array Dataflow Analysis

*Given a read from an array element, what was the last write to the same array element before the read?*

Simple case: array written through a single reference

```
for (i = 0; i < N; ++i)
    for (j = 0; j < N - i; ++j)
F:     a[i+j] = f(a[i+j]);
for (i = 0; i < N; ++i)
W:     Write(a[i]);
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Access relations:

```
A1 := [N] -> { F[i, j] -> a[i+j] : 0 <= i < N and 0 <= j < N - i };
A2 := [N] -> { W[i] -> a[i] : 0 <= i < N };
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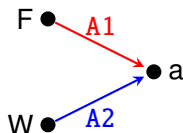
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Map to all writes:  $R := A2 \cdot (A1^{-1})$ ;

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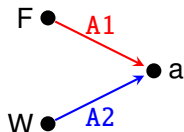
## Standard Array Dataflow Analysis

Given a read from an array element, what was the *last* write to the same array element before the read?

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Last write:  $\text{lexmax } R; \# [N] \rightarrow \{ W[i] \rightarrow F[i, 0] : 0 \leq i < N \}$



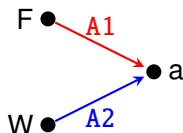
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Last write:  $\text{lexmax } R; \# [N] \rightarrow \{ W[i] \rightarrow F[i, 0] : 0 \leq i < N \}$

In general: impose lexicographical order on shared iterators

# Standard Array Dataflow Analysis

## Multiple Potential Sources

- Dataflow is typically performed per read access (“sink”)  $C$
- Corresponding writes (“potential sources”)  $P$  are considered in turn
- Map to all potential source iterations:  $D_{C,P}^{\text{mem}} = (A_P^{-1} \circ A_C) \cap B_C^P$   
 (“memory based dependences”;  $B_C^P$ :  $P$  executed before  $C$ )
- Source may already be known for some sink iterations  
 $\Rightarrow$  compute *partial* lexicographical maximum

$$(U', D) = \text{lexmax}_U M$$

$U$ : sink iterations for which no source has been found

$M$ : part of memory based dependences for particular potential source

$$U' = U \setminus \text{dom } M$$

$$M' = \text{lexmax}(M \cap (U \rightarrow \text{ran } M))$$

Note: here, dependence relations map sink iterations to source iterations

# Fuzzy Array Dataflow Analysis

- Introduces **parameters** for each `lexmax` involving dynamic behavior
- Parameters represent dynamic solution of `lexmax` operation
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Main problem for deriving process networks:

Introduces too many parameters

⇒ too many control channels

# On Demand Parametric Array Dataflow Analysis

Similar to FADA:

- Exact, possibly parametric, dataflow
- Introduces parameters to represent dynamic behavior

But:

- + Parameters have a different meaning
- + Effect analyzed before parameters are introduced
- + All computations are performed directly on affine sets and maps
- Currently only supports dynamic conditions

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## Representing Generic Dynamic Conditions

```
while (1) {  
    sample = radioFrontend();  
    if (t(state)) {  
D:        state = detect(sample);  
    } else { /* ... */ }  
}
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Dynamic condition ( $t(\text{state})$ ) represented by *filter*

- Filter access relation(s):  
access to (virtual) array representing condition

$$\{ D(i) \rightarrow (S_0(i) \rightarrow t_0(i)) \}$$

- Filter value relation:  
values of filter array elements for which statement is executed

$$\{ D(i) \rightarrow (1) \mid i \geq 0 \}$$

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access to (virtual) array representing condition  $\text{filter array}$

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## Representing Locally Static Affine Conditions

```
N1: n = f();  
    for (int k = 0; k < 100; ++k) {  
M:   m = g();  
      for (int i = 0; i < m; ++i)  
        for (int j = 0; j < n; ++j)  
A:           a[j][i] = g();  
N2:   n = f();  
      }
```

Values of  $m$  and  $n$  not changed inside  $i$  and  $j$  loops  
⇒ locally static affine loop conditions

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- Filter access relations:

$$\{A(k, i, j) \rightarrow (M(k) \rightarrow m())\}$$

$$\{A(0, i, j) \rightarrow (N1() \rightarrow n())\} \cup \{A(k, i, j) \rightarrow (N2(k-1) \rightarrow n()) \mid k \geq 1\}$$

- Filter value relation:

$$\{A(k, i, j) \rightarrow (m, n) \mid 0 \leq k \leq 99 \wedge 0 \leq i < m \wedge 0 \leq j < n\}$$

Note: filter access relations exploit (static) dataflow analysis on  $m$  and  $n$

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# Overview

- Dataflow analysis performed for each read access (sink) separately
- Potential sources considered from closest to furthest
  - ▶ number of shared loop iterators  $\ell$
  - ▶ textual order
- For each lexmax operation
  - ▶ is it possible for potential source not to execute when sink is executed? (based on filters)
  - ▶ if so, parametrize lexmax problem

## Parametrization

```
state = 0;
while (1) {
    sample = radioFrontend();
    if (t(state)) {
D:      state = detect(sample);
    } else {
C:      decode(sample, &state, &value0);
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**sink C**

**potential source P**

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```

Diagram annotations:

- A red box highlights the `state` argument in the `if (t(state))` condition. A red arrow points from this box to the text "sink C".
- A blue box highlights the `state` variable in the assignment `state = detect(sample);`. A blue arrow points from this box to the text "potential source P".

Memory based dependences:  $D_{C,P}^{\text{mem}} = \{S_0(i) \rightarrow D(i') \mid 0 \leq i' < i\}$

At  $\ell = 1$ :  $M = D_{C,P}^{\text{mem}} \cap \{S_0(i) \rightarrow D(i)\} = \emptyset$

At  $\ell = 0$ :  $M = \{S_0(i) \rightarrow D(i') \mid 0 \leq i' < i\}$

Potential source  $D(i')$  may not have executed even if sink  $S_0(i)$  is executed  
 $\Rightarrow$  parametrization required

# Parameter Representation

Original:

$$M = \{ S_0(i) \rightarrow D(i') \mid 0 \leq i' < i \}$$

After parameter introduction:

$$M' = \{ S_0(i) \rightarrow D(\lambda_C^P(i)) \mid 0 \leq \lambda_C^P(i) < i \wedge \beta_C^P(i) = 1 \}$$

$$\Rightarrow \text{lexmax } M' = M$$

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$$\Rightarrow \text{lexmax } M' = M'$$

Meaning of the parameters:

- $\lambda_C^P(\mathbf{k})$ : last executed iteration of  $D_{C,P}^{\text{mem}}(\mathbf{k})$
- $\beta_C^P(\mathbf{k})$ : any iteration of  $D_{C,P}^{\text{mem}}(\mathbf{k})$  is executed

Note: FADA introduces separate set of parameters for each lexmax

Note:  $\lambda_C^P(\mathbf{k})$  and  $\beta_C^P(\mathbf{k})$  depend on  $\mathbf{k}$ , but dependence can be kept implicit

$$\Rightarrow \lambda_C^P \text{ and } \beta_C^P$$

## Introducing as few Parameters as possible

In principle, the number of elements in  $\lambda$  is equal to the number of iterators  
However, in many cases, we can avoid introducing some of those elements

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```
for (i = 0; i < 100; ++i)
    if (t())
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            A:          a = t();
B: b = a;
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$$M = \{ B() \rightarrow A(i, j) \mid 0 \leq i, j < 100 \}$$

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$$\text{lexmax } M' = \{ B() \rightarrow A(\lambda_0, 99) \mid 0 \leq \lambda_0 < 100 \wedge \beta = 1 \}$$

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- dimensions inside innermost condition that is not static affine
- dimensions that can only attain a single value (for a given value of  $\mathbf{k}$ )

# Introducing as few Parameters as possible

Dimensions that can only attain a single value

```

for (int k = 0; k < 100; ++k) {
N:      N = f();
M:      M = g();
        for (int i = 0; i < N; ++i)
            for (int j = 0; j < M; ++j)
A:                a[i][j] = i + j;
        for (int i = 0; i < N; ++i)
            for (int j = 0; j < M; ++j)
H:                h(i, j, a[i][j]);
}

```

$$D_{H,A}^{\text{mem}} = \{H(k, i, j) \rightarrow A(k', i, j) \mid k' \leq k\}$$

$$\lambda_1(k, i, j) = i$$

$$\lambda_2(k, i, j) = j$$

$\Rightarrow$  no need to introduce  $\lambda_1$  and  $\lambda_2$

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- dimensions before  $\ell$

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Dimensions before  $\ell$

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```

At  $\ell = 1$ :

$$M = \{H(k, i, j) \rightarrow A(k, i, j)\}$$

$\Rightarrow$  no need to introduce  $\lambda_0$  (yet) at  $\ell = 1$



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Note: all sinks are accounted for at  $\ell = 1$

$\Rightarrow$  no need to consider  $\ell = 0$  and  $\lambda_0$  not needed at all

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However, in many cases, we can avoid introducing some of those elements

- dimensions inside innermost condition that is not static affine
- dimensions that can only attain a single value (for a given value of  $\mathbf{k}$ )
- dimensions before  $\ell$

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$\Rightarrow$  replace  $\beta$  by  $\sigma$ : the number of implicitly equal shared iterators

$$\beta = 1 \quad \rightarrow \quad \sigma \geq \ell$$

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- ▶ when moving to  $\ell - 1$ 
  - ★ introduce additional parameter  $\lambda_{\ell-1}$  (if needed)
  - ★ make implicit equality explicit
- ▶ at the end of the dataflow analysis

$$\sigma \geq \ell_{\leq} \quad \rightarrow \quad \beta = 1$$

$$\sigma < \ell_{\leq} \quad \rightarrow \quad \beta = 0$$

( $\ell_{\leq}$ : smallest  $\ell$  for which parametrization was applied)

$\lambda(\mathbf{k})$  and  $\beta(\mathbf{k})$  now refer to last execution of  $\bar{D}(\mathbf{k})$

( $\bar{D}$ : result of projecting out parameters from final dataflow relation)

## When to Introduce Parameters

- Sink  $C$
- Potential source  $P$
- Subset of sink iteration  $U$
- Mapping to potential source iterations  $M$

Computing

$$(U', D) = \operatorname{lexmax}_U M$$

## When to Introduce Parameters

- Sink  $C$
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Computing

$$(U', D) = \operatorname{lexmax}_U M$$

Filter on source contradicts  $F$ 

$$\ell = 1$$

- Potential source filter access relation

$$\{H(i) \rightarrow (N(i) \rightarrow n)\}$$

```
while (1) {
```

```
N:  n = f();
```

```
  a = g(); potential source
```

```
  if (n < 100)
```

```
H:    a = h();
```

```
  if (n > 200)
```

```
T:    t(a);
```

```
}
```

sink

- Potential source filter value relation

$$\{H(i) \rightarrow (n) \mid i \geq 0 \wedge n < 100\}$$

- Sink filter access relation

$$\{T(i) \rightarrow (N(i) \rightarrow n)\}$$

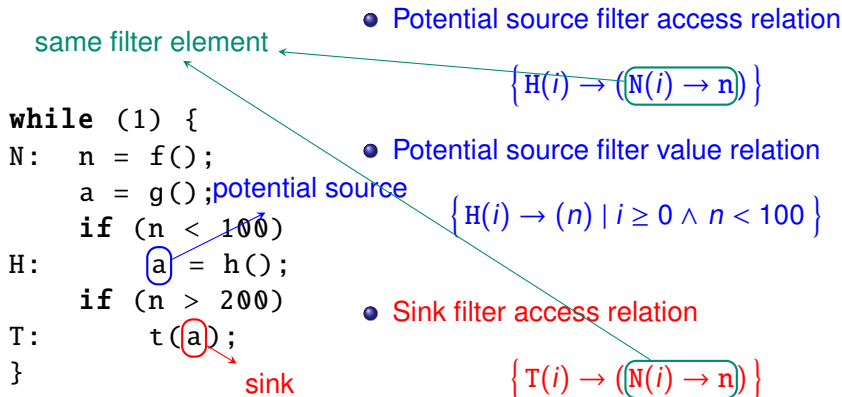
- Sink filter value relation

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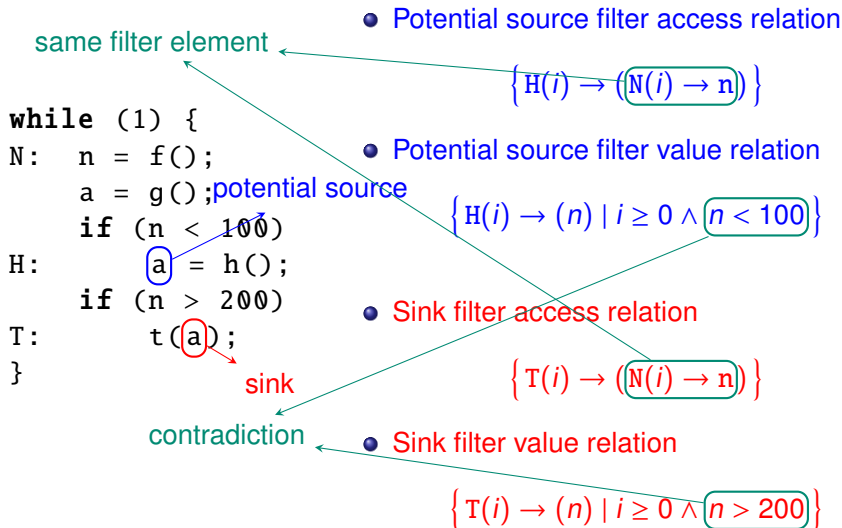
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$$\ell = 1$$



Filter on source contradicts  $F$ 

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$$(U', D) = \operatorname{lexmax}_U M$$

## Filter on source contradicts $F'$

```

N:  n = f();           potential source
    if (n < 100)
H:  a = h();
    if (n < 200)
H2: a = h2();
T:  t(a);
   }

```

sink

$$\text{lexmax}_U M$$

$$M = \{ T() \rightarrow H() \}$$

$$U = \{ T() \mid \sigma^{H2} < 0 \}$$

## Filter on source contradicts $F'$

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N:   n = f();           potential source
     if (n < 100)
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H2 not executed

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   }
```

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$$M = \{ T() \rightarrow H() \}$$

$$U = \{ T() \mid \sigma^{H2} < 0 \}$$

H2 not executed

- Updated sink filter access relation

$$\{ T(i) \rightarrow (N(i) \rightarrow n) \}$$

- Updated sink filter value relation

$$\{ T(i) \rightarrow (n) \mid i \geq 0 \wedge n \geq 200 \}$$

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  - 4 Let  $F'$  be equal to  $F$  updated with information from other sources
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⇒ replace  $M$  by empty relation and stop
  - 6 Filter on source implied by  $F$   
⇒ stop (no parametrization required)

Computing

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# Filter on source implied by $F$

$$\ell = 1$$

- Potential source filter access relation

$$\{H(i) \rightarrow (N(i) \rightarrow n)\}$$

```
while (1) {
```

```
  N:  n = f();
```

```
      a = g(); potential source
```

```
      if (n < 200)
```

```
  H:  (a) = h();
```

```
      if (n < 100)
```

```
  T:  t(a);
```

```
}
```

sink

- Potential source filter value relation

$$\{H(i) \rightarrow (n) \mid i \geq 0 \wedge n < 200\}$$

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  - 6 Filter on source implied by  $F$   
⇒ stop (no parametrization required)
  - 7 Filter on source implied by  $F'$   
⇒ parametrize  $D$  and stop

Computing

$$(U', D) = \operatorname{lexmax}_U M$$

## Filter on source implied by $F'$

N:  $n = f()$ ; potential source

**if** ( $n < 200$ )

H:  $a = h()$ ;

**if** ( $n > 100$ )

H2:  $a = h2()$ ;

T:  $t(a)$ ;

}

sink

$\text{lexmax}_U M$

$M = \{T() \rightarrow H()\}$

$U = \{T() \mid \sigma^{H2} < 0\}$

- Updated sink filter access relation

$$\{T(i) \rightarrow (N(i) \rightarrow n)\}$$

- Updated sink filter value relation

$$\{T(i) \rightarrow (n) \mid i \geq 0 \wedge n \leq 100\}$$

## When to Introduce Parameters

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 $\Rightarrow$  stop (no parametrization required)
  - 7 Filter on source implied by  $F'$   
 $\Rightarrow$  parametrize  $D$  and stop
  - 8 Parametrize  $M$

Computing

$$(U', D) = \operatorname{lexmax}_U M$$

## Additional Constraints on Parameters

- Some source iterations are definitely executed  
⇒  $\lambda$  no later than definitely executed iterations



## Additional Constraints on Parameters

- Some source iterations are definitely executed  
⇒  $\lambda$  no later than definitely executed iterations
- Eliminate (some) conflicts with other parameters

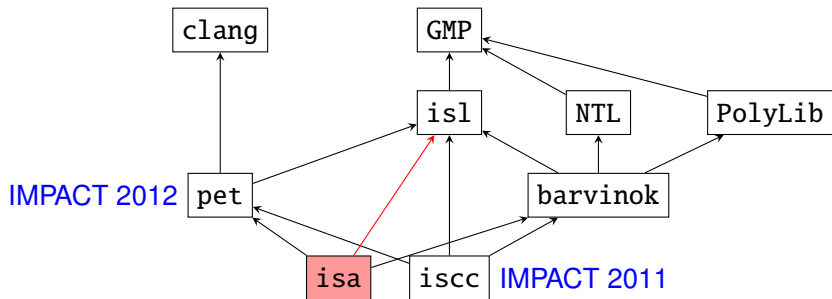
```
state = 0;
while (1) {
    sample = radioFrontend();
    if (t(state)) {
D:        state = detect(sample);
    } else {
C:        decode(sample, &state, &value0);
           value1 = processSample0(value0);
           processSample1(value1);
    }
}
```

⇒  $\lambda_0^C(i)$  and  $\lambda_0^D(i)$  cannot both be smaller than  $i - 1$

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## Interaction with Libraries



isl: manipulates parametric affine sets and relations

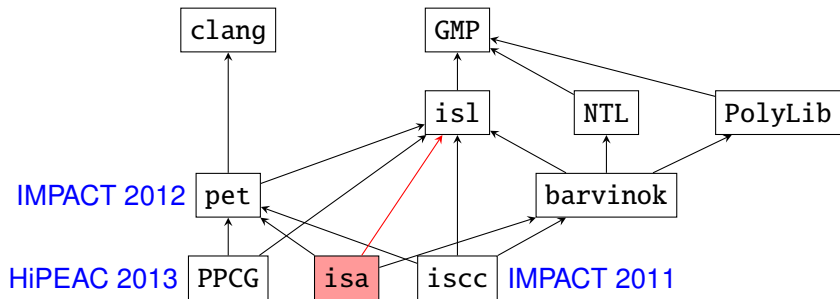
barvinok: counts elements in parametric affine sets and relations

pet: extracts polyhedral model from clang AST

isa: prototype tool set including

- derivation of process networks (with **On Demand Parametric ADA**)
- equivalence checker

## Interaction with Libraries



isl: manipulates parametric affine sets and relations

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pet: extracts polyhedral model from clang AST

isa: prototype tool set including

- derivation of process networks (with **On Demand Parametric ADA**)
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PPCG: Polyhedral Parallel Code Generator

## Related Work

- Fuzzy Array Dataflow Analysis
  - ⇒ only known publicly available implementation: `fadataool`
- Pugh et al. (1994) and Maslov (1995) produce approximate results
- Collard et al. (1999)
  - ▶ handle unstructured programs
  - ▶ only collect constraints
  - ▶ assume  $\Omega$  can solve the constraints, but it cannot

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# Experimental Results

input	da			fadatool			fadatool -s		
	time	p	d	time	p	l	time	p	l
Example from paper	0.01s	0	5	0.01s	6	6	0.01s	6	6
Example from slides	0.01s	4	9	0.01s	6	16	incorrect		
fuzzy4	0.06s	3	9	0.02s	4	9	0.01s	0	9
for1	0.02s	2	3	0.01s	4	46	0.02s	2	3
for2	0.03s	2	3	0.09s	12	5k	0.04s	4	3
for3	0.04s	2	3	42s	24	1M	0.08s	6	3
for4	0.06s	2	3				0.16s	8	3
for5	0.08s	2	3				0.25s	10	3
for6	0.14s	2	3				0.42s	12	3
cascade_if1	0.02s	2	3	0.01s	2	4	0.01s	2	4
cascade_if2	0.02s	2	10	0.02s	4	52	0.02s	2	8
cascade_if3	0.03s	2	22	0.03s	6	723	0.36s	3	16
cascade_if4	0.02s	2	10	0.17s	8	9k	1m	4	28
while1	0.01s	0	4	0.00s	1	4	0.01s	0	4
while2	0.03s	3	4	0.01s	5	6	incorrect		
if_var	0.03s	4	3	0.01s	2	8	0.01s	2	4
if_while	0.04s	2	14	0.01s	5	58	0.02s	4	58
if2	0.02s	2	2	0.46s	12	29k	0.04s	4	2

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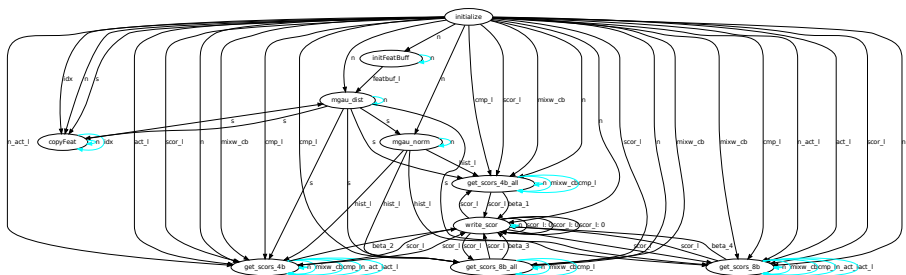
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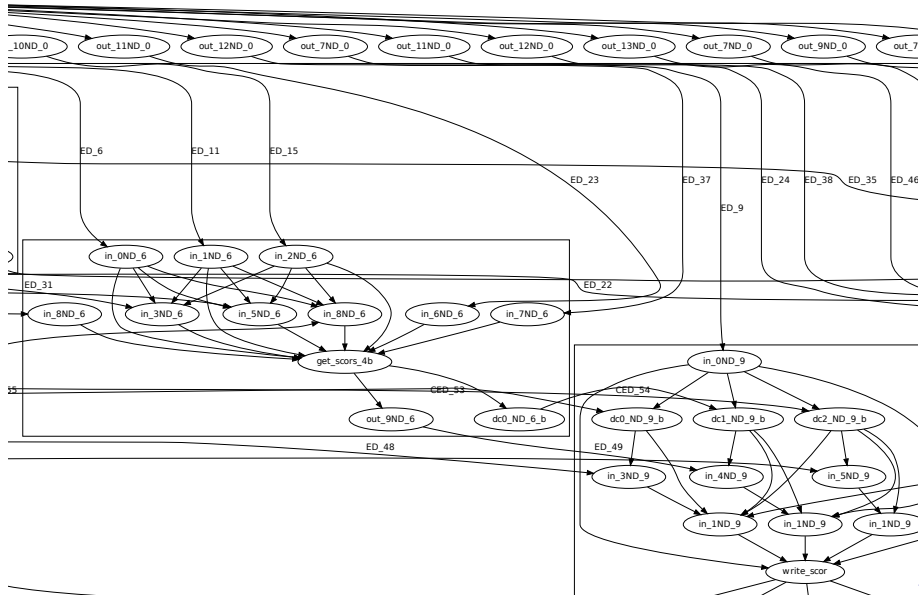
## Larger Example — Input

```
for (j = 1; j <= frame; j++) {
    initialize(frame, n_act, &scor, &act, &ps, cmp,
               &s, &n, &idx, &mixw_cb, &cmp_l, &n_act_l, &act_l, &scor_l)
    for (i = 0; i < n; ++i) {
        initFeatBuff(i, &feat_buff, &featbuf_l);
        copyFeat(&s, frame, i, idx, &s);
        mgau_dist(&s, frame, i, &featbuf_l, &s);
        hist_l = mgau_norm(&s, frame, i);
        if (mixw_cb >= 1) {
            if (cmp_l >= 1)
                get_scor_4b_all(&s, i, hist_l, &scor_l, &scor_l);
            else
                get_scor_4b(&s, i, hist_l, n_act_l, &act_l, &scor_l, &scor_l);
        } else {
            if (cmp_l >= 1)
                get_scor_8b_all(&s, i, hist_l, &scor_l, &scor_l);
            else
                get_scor_8b(&s, i, hist_l, n_act_l, &act_l, &scor_l, &scor_l);
        }
        write_scor(&scor_l, &scor_l);
    }
}
```

# Larger Example — Dataflow Graph



# Larger Example — (Partial) Process Network



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# Conclusion

## Conclusions

- Dynamic behavior represented using “filters”
- Exact, possibly parametric, dataflow analysis
- Prototype implementation in `isa`
- Similar to FADA, but
  - ▶ Parameters have a different meaning
  - ▶ Effect analyzed before parameters are introduced
  - ▶ All computations are performed directly on affine sets and maps

## Future work

- Tighter integration into `pet`