

Program Adaptivity Analysis

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1 Low Level Control Flow Based Language

We first consider a low level language where the queries are atomic and the dependency relations are caused only by control flow.

1.1 Syntax and Semantics

Syntax.

Arithmetic Operators	$*_a ::= + \mid - \mid \times \mid \div$
Boolean Operators	$*_b$
Relational Operators	$*_r ::= < \mid \leq \mid =$
Label	l
While Map	$w \in \text{Label} \times \mathbb{N}$
AExpr	$a ::= n \mid x \mid a *_a a \mid [] \mid [a_0, \dots, a_i]$
BExpr	$b ::= \text{true} \mid \text{false} \mid \neg b \mid b *_b b \mid a *_r a$
Expr	$e ::= a \mid b$
Command	$c ::= [x \leftarrow e]^l \mid [x \leftarrow q]^l \mid [\text{switch}(e, x, (v_i \rightarrow q_i))]^l \mid \text{loop } [e_N]^l (f) \text{ do } c \mid c; c \mid \text{if}([b]^l, c_1, c_2) \mid \text{while}([b]^l, c) \mid [\text{skip}]^l$
Query	$q ::= q_0, q_1, \dots, q_n$
Memory	$m ::= [] \mid m[x^l \rightarrow v]$
Trace	$t ::= [] \mid [(q^{(l,w)}, v)] \mid t ++ t$

Operational Semantics.

$$\langle m, a \rangle \rightarrow_a a' : \text{Memory} \times \text{AExpr} \Rightarrow \text{AExpr}$$

$$\frac{}{\langle m, x \rangle \rightarrow_a m(x)} \quad \frac{\langle m, a_1 \rangle \rightarrow_a a'_1}{\langle m, a_1 *_a a_2 \rangle \rightarrow_a e'_1 *_a a_2} \quad \frac{\langle m, a_2 \rangle \rightarrow_a a'_2}{\langle m, n_1 *_a a_2 \rangle \rightarrow_a n_1 *_a a'_2}$$

$$\frac{n_3 = n_1 *_a n_2}{\langle m, n_1 *_a n_2 \rangle \rightarrow_a n_3}$$

$$\langle m, b \rangle \rightarrow_b b' : \text{Memory} \times \text{BExpr} \Rightarrow \text{BExpr}$$

$$\frac{}{\langle m, \text{true} \rangle \rightarrow_b \text{true}} \quad \frac{}{\langle m, \text{false} \rangle \rightarrow_b \text{false}} \quad \frac{\langle m, a_1 \rangle \rightarrow_a a'_1}{\langle m, a_1 *_r a_2 \rangle \rightarrow_b e'_1 *_r a_2}$$

$$\frac{\langle m, a_2 \rangle \rightarrow_a a'_2}{\langle m, n_1 *_r a_2 \rangle \rightarrow_b n_1 *_r a'_2} \quad \frac{b_3 = n_1 *_r n_2}{\langle m, n_1 *_r n_2 \rangle \rightarrow_b b_3} \quad \frac{\langle m, b_1 \rangle \rightarrow_b b'_1}{\langle m, b_1 *_b b_2 \rangle \rightarrow_b b'_1 *_b b_2}$$

$$\frac{\langle m, b_2 \rangle \rightarrow_b b'_2}{\langle m, \text{true} *_b b_2 \rangle \rightarrow_b \text{true} *_b b'_2} \quad \frac{\langle m, b_2 \rangle \rightarrow_b b'_2}{\langle m, \text{false} *_b b_2 \rangle \rightarrow_b \text{false} *_b b'_2} \quad \frac{\langle m, b \rangle \rightarrow_b b'}{\langle m, \neg b \rangle \rightarrow_b \neg b'}$$

$$\boxed{\langle m, c, t \rangle \rightarrow \langle m', c', t' \rangle}$$

$$Memory \times Com \times Trace \times WhileMap \Rightarrow Memory \times Com \times Trace \times WhileMap$$

$$\begin{array}{c}
\frac{q(D) = v}{\langle m, [x \leftarrow q]^l, t, w \rangle \rightarrow \langle m[v/x], \text{skip}, t++[(q^{(l,w)}, v)], w \rangle} \text{query} \\
\\
\frac{m, e \Rightarrow e'}{\langle m, [x \leftarrow e]^l, t, w \rangle \rightarrow \langle m, [x \leftarrow e']^l, t, w \rangle} \text{assn1} \quad \frac{}{\langle m, [x \leftarrow v]^l, t, w \rangle \rightarrow \langle m[v/x], [\text{skip}]^l, t, w \rangle} \text{assn2} \\
\\
\frac{\langle m, c_1, t, w \rangle \rightarrow \langle m', c'_1, t', w \rangle}{\langle m, c_1; c_2, t, w \rangle \rightarrow \langle m', c'_1; c_2, t', w \rangle} \text{seq1} \quad \frac{}{\langle m, [\text{skip}]^l; c_2, t, w \rangle \rightarrow \langle m, c_2, t, w \rangle} \text{seq2} \\
\\
\frac{\langle m, b \rangle \rightarrow_b b'}{\langle m, \text{if}([b]^l, c_1, c_2), t, w \rangle \rightarrow \langle m, \text{if}([b']^l, c_1, c_2), t, w \rangle} \text{if} \\
\\
\frac{}{\langle m, \text{if}([\text{true}]^l, c_1, c_2), t, w \rangle \rightarrow \langle m, c_1, t, w \rangle} \text{if-t} \quad \frac{}{\langle m, \text{if}([\text{false}]^l, c_1, c_2), t, w \rangle \rightarrow \langle m, c_2, t, w \rangle} \text{if-f} \\
\\
\frac{\langle m, e \rangle \rightarrow e'}{\langle m, [\text{switch}(e, x, (v_i \rightarrow q_i))]^l, t, w \rangle \rightarrow \langle m, [\text{switch}(e', x, (v_i \rightarrow q_i))]^l, t, w \rangle} \text{switch} \\
\\
\frac{}{\langle m, [\text{switch}(v_k, x, (v_i \rightarrow q_i))]^l, t, w \rangle \rightarrow \langle m, [x \leftarrow q_k]^l, t, w \rangle} \text{switch-v} \\
\\
\frac{\langle m, e_N \rightarrow e'_N \rangle}{\langle m, \text{loop}[e_N]^l(f) \text{ do } c, t, w \rangle \rightarrow \langle m, [\text{loop}[e'_N]^l(f) \text{ do } c]^l, t, w \rangle} \text{loop} \\
\\
\frac{v_N > 0}{\langle m, \text{loop}[v_N]^l(f) \text{ do } c, t, w \rangle \rightarrow \langle m, c; \text{loop}[(v_N - 1)]^l(f) \text{ do } c, t, (w + l) \rangle} \text{loop-t} \\
\\
\frac{v_N = 0}{\langle m, \text{loop}[v_N]^l(f) \text{ do } c, t, w \rangle \rightarrow \langle m, [\text{skip}]^l, t, (w \setminus l) \rangle} \text{loop-f}
\end{array}$$

where w_l refers to a map w without the key l .

$$\begin{array}{lll}
w \setminus l & = w & l \notin \text{Keys}(w) \\
& = w_l & \text{Otherwise} \\
w + l & = w[l \rightarrow 0] & l \notin \text{Keys}(w) \\
& w_l[l \rightarrow w(l) + 1] & \text{Otherwise}
\end{array}$$

1.2 Adaptivity of Programs in Low level language

Definition 1 (Label Order). $<_w$ and $=_w$.

$$\begin{aligned} w_1 =_w w_2 &\triangleq Keys(w_1) = Keys(w_2) \wedge \forall k \in Keys(w_1). w_1(k) = w_2(k) \\ \emptyset =_w \emptyset \end{aligned}$$

$$mk(w_i) = MinKey(w_i)$$

$$\begin{aligned} w_1 <_w w_2 &\triangleq & w_1 = \emptyset \\ &\triangleq mk(w_1) < mk(w_2) & w_1, w_2 \neq \emptyset \\ &\triangleq w_1(mk(w_1)) < w_2(mk(w_2)) & mk(w_1) = mk(w_2) \\ &\triangleq (w_1 \setminus mk(w_1)) <_w (w_2 \setminus mk(w_2)) & \text{Otherwise} \end{aligned}$$

Definition 2 (Query Direction). *Direction between two queries.*

$\forall q_1, q_2, l_1, l_2, w_1, w_2. (q_1^{l_1, w_1}) \text{TO} (q_2^{l_2, w_2})$, denoted as $\text{To}(q_1^{l_1, w_1}, q_2^{l_2, w_2})$

iff $(q_1^{l_1, w_1}) <_q (q_2^{l_2, w_2})$

where

$(q_1^{l_1, w_1}) <_q (q_2^{l_2, w_2})$ is defined:

$$\begin{aligned} l_1 < l_2 & \quad w_1 = \emptyset \vee w_2 = \emptyset \vee w_1 =_w w_2 \\ w_1 <_w w_2 & \quad \text{Otherwise} \end{aligned}$$

Independence between two queries in Low level language When two queries q_1, q_2 are independent in a program c , suppose q_1 appears before q_2 in the program c , we think the choice of queries starting from q_1 , ending with query q_2 should be fixed no matter the change of the result of q_1 .

Definition 3 (Query Independence). *Two queries q_i and q_j in a program c are independent, $\text{IND}(q_i^{(l_1, w_1)}, q_j^{(l_2, w_2)}, c) =$.*

$$\begin{aligned} \forall m, D. \langle m, c, [] \rangle \rightarrow^* \langle m_1, c_1, t_1 \rangle \rightarrow \langle m_2, c_2, t_1 + [(q_i^{(l_1, w_1)}, v_i)] \rangle \rightarrow^* \langle m_3, \text{skip}, t_3 \rangle \wedge x = \text{FindVar}(q_i^{(l_1, w_1)}, c) \wedge \\ w_1 = \emptyset \implies \left(\begin{aligned} & \left((q_i^{(l_1, w_1)}, v_i) \in t_3 \wedge (q_j^{(l_2, w_2)}, v_j) \in t_3 \implies \forall v \in \text{codomain}(q_i^{l_1}). \left(\langle m, c[v/q_i], [] \rangle \rightarrow^* \langle m', \text{skip}, t' \rangle \wedge (q_j^{l_2}, v_j) \in t' \right) \right) \\ & \wedge \left((q_i^{l_1}, v_i) \in t_3 \wedge (q_j^{l_2}, v_j) \notin t_3 \implies \forall v \in \text{codomain}(q_i^{l_1}). \left(\langle m, c[v/q_i], [] \rangle \rightarrow^* \langle m', \text{skip}, t' \rangle \wedge (q_j^{l_2}, v_j) \notin t' \right) \right) \end{aligned} \right) \\ \wedge w_1 \neq \emptyset \implies \left(\begin{aligned} & ((q_i^{(l_1, w_1)}, v_i) \in t_3 \wedge (q_j^{(l_2, w_2)}, v_j) \in t_3 \implies \\ & \quad \forall v \in \text{codomain}(q_i^{l_1}). \left(\langle m_2[v/x], c_2, t_1 + [(q_i^{(l_1, w_1)}, v_i)] \rangle \rightarrow^* \langle m', \text{skip}, t' \rangle \wedge (q_j^{l_2}, v_j) \in t' \right) \\ & \quad \wedge ((q_i^{l_1}, v_i) \in t \wedge (q_j^{l_2}, v_j) \notin t \implies \\ & \quad \quad \forall v \in \text{codomain}(q_i^{l_1}). \left(\langle m_2[v/x], c_2, t_1 + [(q_i^{(l_1, w_1)}, v_i)] \rangle \rightarrow^* \langle m', \text{skip}, t' \rangle \wedge (q_j^{l_2}, v_j) \notin t' \right) \end{aligned} \right) \end{aligned}$$

In following examples:

$$\begin{aligned} c_1 \triangleq & \begin{aligned} & [x \leftarrow q_1]^1; \\ & \text{if } [x]^2 \\ & \text{then } [y \leftarrow q_2]^3 \\ & \text{else } [y \leftarrow 0]^4; \\ & \text{if } [x]^5 \\ & \text{then } [y \leftarrow 0]^6 \\ & \text{else } [y \leftarrow q_2]^7; \end{aligned} \\ c_2 \triangleq & \begin{aligned} & [x \leftarrow q_1]^1; \\ & \text{if } [x]^2 \\ & \text{then } [y \leftarrow q_2]^3 \\ & \text{else } [y \leftarrow q_3]^4; \\ & [z \leftarrow q_2]^5; \end{aligned} \\ c_3 \triangleq & \begin{aligned} & [x \leftarrow q_1]^1; \\ & \text{if } [x]^2 \\ & \text{then } [y \leftarrow q_3]^3 \\ & \text{else } [y \leftarrow q_4]^4; \\ & [z \leftarrow q_2]^5; \end{aligned} \\ c_4 \triangleq & \begin{aligned} & [x \leftarrow q_1]^1; \\ & [y \leftarrow q_2]^2; \\ & \text{if } [x + y = 5]^3 \\ & \text{then } [z \leftarrow q_3]^4 \\ & \text{else } [\text{skip}]^5; \\ & [w \leftarrow q_4]^6; \end{aligned} \end{aligned}$$

We have the dependency as:

In program c_1 : $\text{IND}(q_2^3, q_2^7, c_1)$,

In program c_2 : $\text{IND}(q_1^1, q_2^5, c_2)$, $\text{IND}(q_2^3, q_3^4, c_2)$,

In program c_3 : $\text{IND}(q_1^1, q_2^5, c_3)$, $\text{IND}(q_3^3, q_4^4, c_3)$,

In program c_4 : $\text{IND}(q_1^1, q_2^2, c_4)$, $\text{IND}(q_3^3, q_4^4, c_4)$, $\text{IND}(q_1^1, q_4^4, c_4)$, $\text{IND}(q_2^2, q_4^4, c_4)$,

In following examples containing `while` loop:

$$\begin{array}{lll}
 c_1 \triangleq \begin{array}{l} [x \leftarrow q_1]^1; \\ \text{while}([x \leq 100]^2, \\ [x \leftarrow q_2 + x]^3); \end{array} & c_2 \triangleq \begin{array}{l} [x \leftarrow q_1]^1; \\ \text{while}([x \leq 100]^2, \\ [y \leftarrow q_2]^3; \\ [z \leftarrow q_3]^4; \\ [x \leftarrow y + z + x]^5); \end{array} & c_3 \triangleq \begin{array}{l} [x \leftarrow q_1]^1; \\ \text{while}([x \leq 100]^2, \\ [y \leftarrow q_2 + x]^3; \\ \text{while}([y \leq 50]^4, \\ [z \leftarrow q_3]^5; \\ [y \leftarrow y + z]^6; \\ [x \leftarrow y + x]^7); \end{array}
 \end{array}$$

we have the dependency as:

In program c_1 : No independent queries.

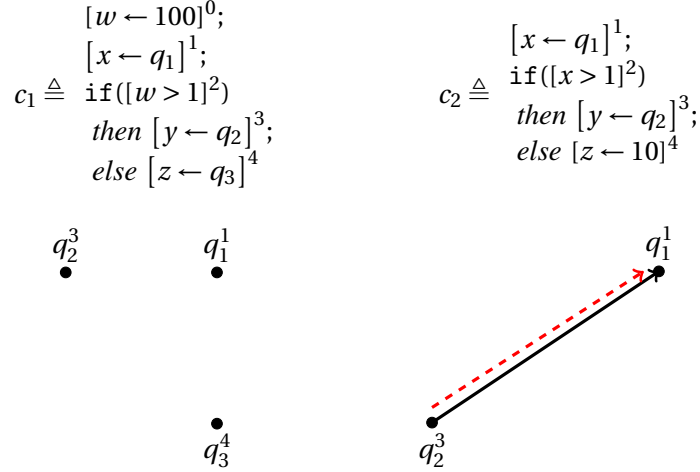
In program c_2 : $\text{IND}(q_2^{(3,l)}, q_3^{(4,l)}, c_2)$ for all l .

In program c_3 : No independent queries.

Dependency between multiple queries

Example 1.1. *Dependency graphs for programs containing 3 atomic queries*

Let $q_1 \triangleq \lambda D.D_1 * D_j$, $q_2 \triangleq \lambda D.D_3 * D_4$ and $q_3 \triangleq \lambda D.D_3 * D_2$. in program c_1 and c_2 as follows:



2 High level Language

2.1 Syntax and Semantics

Syntax.

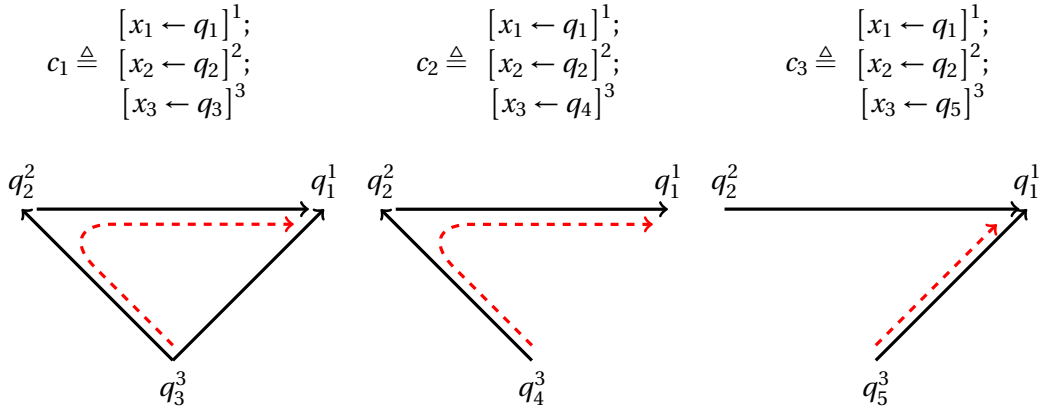
Arithmetic Operators	$*_a ::= + \mid - \mid \times \mid \div$
Boolean Operators	$*_b$
Relational Operators	$*_r ::= < \mid \leq \mid =$
Label	l
While Map	$w \in \text{Label} \times \mathbb{N}$
AExpr	$a ::= n \mid x \mid a *_a a \mid [] \mid [a_0, \dots, a_i]$
BExpr	$b ::= \text{true} \mid \text{false} \mid \neg b \mid b *_b b \mid a *_r a$
Command	$c ::= [x \leftarrow e]^l \mid [x \leftarrow q(e)]^l$ $\mid c; c \mid \text{if}([b]^l, c_1, c_2) \mid \text{while}([b]^l, c) \mid [\text{skip}]^l \mid \text{loop } [v_N]^l (f) \text{ do } c$
Memory	$m ::= [] \mid m[x^l \rightarrow v]$
Trace	$t ::= [] \mid [(q^{(l,w)}, v)] \mid t ++ t$

Example 2.1. Dependency graphs for high level programs containing non-atomic queries

Let $q_1 = \lambda D.D_i * D_j$,

Let $q_2(x_1) = \lambda D.D_i * D_j + x_1$.

Let $q_3(x_1 - x_2) = \lambda D.D_i * D_j + x_1 - x_2$, $q_4(x_2) = \lambda D.D_i * D_j + x_2$, and $q_5(x_1) = \lambda D.D_i * D_j + x_1$.
in program c_1 , c_2 and c_3 as following:



2.2 Rewriting from High Level Program into Low Level Program

The transformation $\langle e^h \rangle = e^l$ transfers the expression e^h in the high level language to an expression e^l in the low language. Let us look at the special cases: the query.

In the first transition, if a query in high level language isn't atomic, i.e., $q(e)$ depends on e with free variables, then it will be rewrite into a switch command. This rewriting will switch on the possible values v_i of e and convert the $q(e)$ into a series of atomic queries q_i .

In the second transition, if a query in high level language is atomic, $q()$ only depends on data base D and some constant values, then it will be rewrite into identity in our low level language.

Another special case is the sampling command in high level language. To exclude the dependency caused by the randomness, we will rewrite the sampling into an assignment command in low level

language. This will assign a constant value to the corresponding variable.
The resting commands will be rewrote identically.

$$\begin{aligned}
\langle [x \leftarrow q(e)]^l \rangle &\Rightarrow \left[\text{switch} \left(e, x, \begin{pmatrix} v_1 \rightarrow q_1, \\ \cdots, \\ v_m \rightarrow q_m \end{pmatrix} \right) \right]^l \\
\langle q() \rangle &\Rightarrow q \\
\langle [x \leftarrow \text{uniform}]^l \rangle &\Rightarrow [x \leftarrow c_u]^l \\
\langle [x \leftarrow e]^l \rangle &\Rightarrow [x \leftarrow e]^l \\
\langle c_1; c_2 \rangle &\Rightarrow \langle c_1 \rangle; \langle c_2 \rangle \\
\langle \text{if}([b]^l, c_1, c_2) \rangle &\Rightarrow \text{if}([b]^l, \langle c_1 \rangle, \langle c_2 \rangle) \\
\langle \text{while}([b]^l, c) \rangle &\Rightarrow \text{while}([b]^l, \langle c \rangle)
\end{aligned}$$

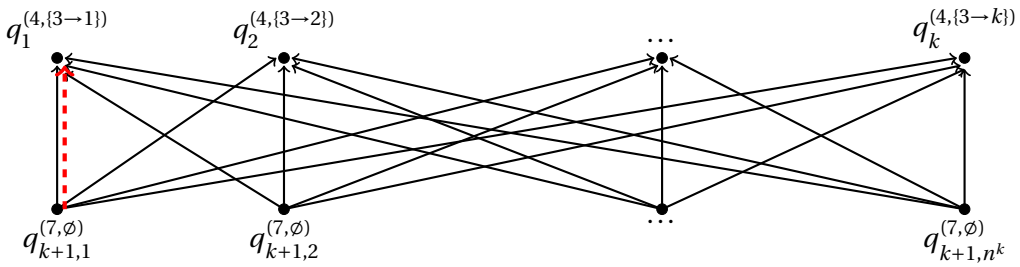
Example 2.2 (Two Round Algorithm).

$$\begin{aligned}
&\begin{aligned}
&[j \leftarrow 1]^1; \\
&[a \leftarrow []]^2; \\
&\text{while}([j \leq k]^3, \\
&\quad [x \leftarrow q_j 0]^4; \\
&\quad [a \leftarrow x :: a]^5; \\
&\quad [j \leftarrow j + 1]^6; \\
&\quad [l \leftarrow q_{k+1}(a)]^7;
\end{aligned}
\end{aligned}
\Rightarrow
\begin{aligned}
&\begin{aligned}
&[j \leftarrow 1]^1; \\
&[a \leftarrow []]^2; \\
&\text{while}([j \leq k]^3, \\
&\quad [x \leftarrow q_j]^4; \\
&\quad [a \leftarrow x :: a]^5; \\
&\quad [j \leftarrow j + 1]^6; \\
&\quad \left[\text{switch} \left(a, x, \begin{pmatrix} [-n, -n, -n, \dots, -n] \rightarrow q_{k+1,1}, \\ \cdots \\ [n, n, n, \dots, n] \rightarrow q_{k+1, n^k} \end{pmatrix} \right) \right]^7
\end{aligned}
\end{aligned}$$

$$\langle \emptyset, TR^L, D, [], \emptyset \rangle \rightarrow \langle m, \text{skip}, D, t, w \rangle.$$

$$t = [(q_1^{(4, \{3 \rightarrow 1\})}, v_1), (q_2^{(4, \{3 \rightarrow 2\})}, v_2), \dots, (q_k^{(4, \{3 \rightarrow k\})}, v_k), (q_{k+1, i}^{(7, \emptyset)}, v_1)]$$

$$A(TR^L) = I$$



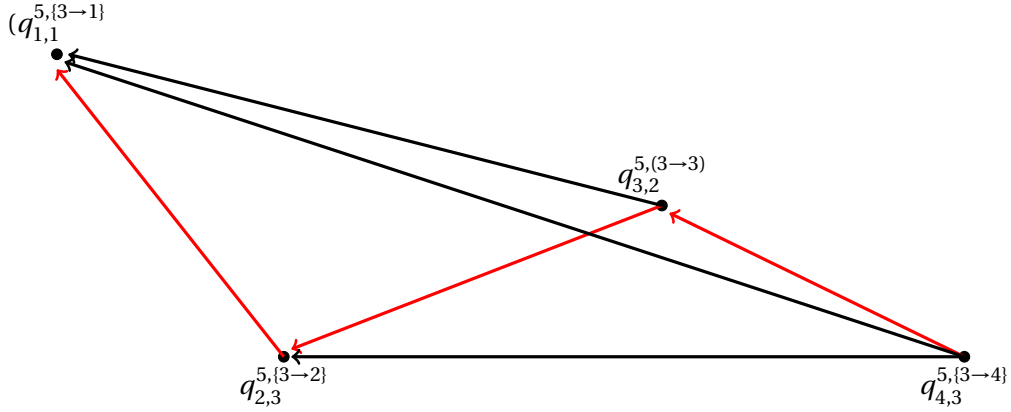
Example 2.3 (Multi-Round Algorithm).

$$\begin{aligned}
 MR^H \triangleq & \begin{aligned} & [j \leftarrow 0]^1; \\ & [I \leftarrow []]^2; \\ & \text{while}([j \leq k]^3, \\ & \quad [p \leftarrow \text{uniform}(0,1)]^4; \\ & \quad [a \leftarrow q_j(p,D)]^5; \\ & \quad [I \leftarrow \text{update}(I, (a,p))]^6; \\ & \quad [j \leftarrow j+1]^7); \end{aligned} \quad \Rightarrow \quad MR^L \triangleq \begin{aligned} & [j \leftarrow 0]^1; \\ & [I \leftarrow []]^2; \\ & \text{while}([j \leq k]^3, \\ & \quad [p \leftarrow 0]^4; \\ & \quad \left[\text{switch} \left(I, x \begin{pmatrix} [] \rightarrow q_{j,1}, \\ \dots \\ [1,2,3,\dots,n] \rightarrow q_{j,n!} \end{pmatrix} \right) \right]^5 \\ & \quad [I \leftarrow \text{update}(I, (a,p))]^6; \\ & \quad [j \leftarrow j+1]^7); \end{aligned}
 \end{aligned}$$

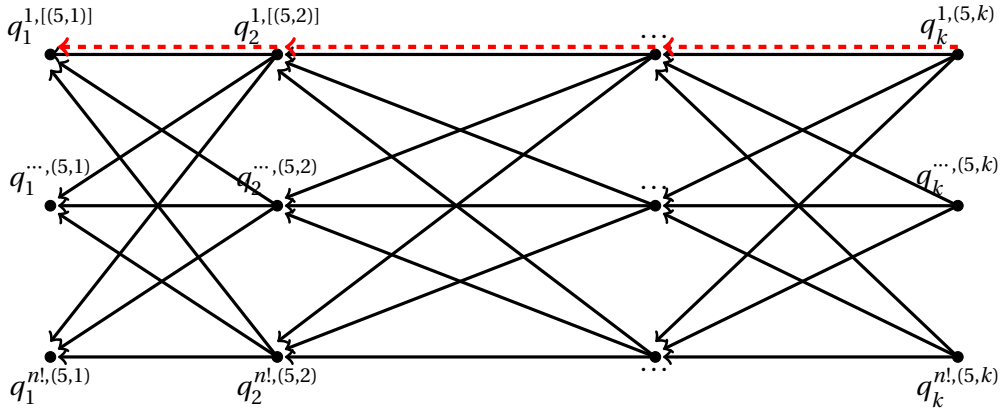
Let $k = 4$, given a specific database D , we have $\langle \emptyset, MR^L, D, [], \emptyset \rangle \rightarrow \langle m, \text{skip}, D, t, w \rangle$ and the trace as:

$$t = \left[(q_{1,1}^{5,\{3 \rightarrow 1\}}, v_1), (q_{2,3}^{5,\{3 \rightarrow 2\}}, v_2), (q_{3,2}^{5,\{3 \rightarrow 3\}}, v_3), (q_{4,3}^{5,\{3 \rightarrow 4\}}, v_4) \right]$$

$$A(TR^L) = 3$$



$\forall k. \forall D$, we have $A(TR^L) = (k - 1)$ given all possible execution traces.



3 Towards Probability

3.1 Syntax and Semantics

Syntax.

Arithmetic Operators	$*_a ::= + \mid - \mid \times \mid \div$
Boolean Operators	$*_b ::= \vee \mid \wedge$
Relational Operators	$*_r ::= < \mid \leq \mid =$
Label	l
While Map	$w \in \text{Label} \times \mathbb{N} \triangleq w + l \mid w \setminus l \mid w \oplus_\rho w$
AExpr	$a ::= n \mid x \mid a *_a a \mid [] \mid [a_0, \dots, a_i] \mid a \times a$
BExpr	$b ::= \text{true} \mid \text{false} \mid \neg b \mid b *_b b \mid a *_r a$
Deterministic Expr	$e_d ::= a \mid b$
Randomized AExpr	$a_r ::= x_r \mid n \mid a_r *_a a_r$
Randomized BExpr	$b_r ::= \neg b_r \mid b_r *_b b_r \mid a_r *_r a_r$
Randomized Expr	$e_r ::= e_d \mid a_r \mid b_r$
Command	$C ::= [x \leftarrow e_d]^l \mid [x_r \leftarrow e_r]^l \mid [x \leftarrow q]^l \mid [x_r \leftarrow \text{uniform}]^l \mid [x_r \leftarrow \text{bernoulli}]^l \mid P; P \mid \text{if}_D([b]^l, P_1, P_2) \mid \text{if}_R([b_r]^l, P_1, P_2) \mid \text{while}([b]^l, P) \mid [\text{skip}]^l \mid \text{unfold}([b]^l, P) \mid [\text{switch}(e, x, (v_i \rightarrow q_i))]^l \mid \text{loop } [v_N]^l (f) \text{ do } P$
Memory	$m ::= [] \mid m[x^l \rightarrow v]$
Trace	$t ::= [] \mid [(q^{(l,w)}, v)] \mid t ++ t$

$$w \setminus l = \begin{cases} w & l \notin \text{Keys}(w) \\ w_l & \text{Otherwise} \end{cases}$$

$$w + l = \begin{cases} w[l \rightarrow 0] & l \notin \text{Keys}(w) \\ w_l[l \rightarrow w(l) + 1] & \text{Otherwise} \end{cases}$$

Semantics We have a countable set RV of random variables ($x_r \in \text{RV}$), a countable set Val of values. For any subset $S \subseteq \text{RV}$, we denote $\text{RanM}[S] \triangleq S \rightarrow \text{Val}$. We let DV as a countable set of deterministic variables (x) and the deterministic memory $\text{DetM} \triangleq \text{DV} \rightarrow \text{Val}$. Distribution over A as $D(A)$. The *distribution unit* $\text{unit} : A \rightarrow D(A)$. The *distribution bind* $\text{bind} : D(A) \rightarrow (A \rightarrow D(B)) \rightarrow D(B)$. $\llbracket C \rrbracket : (\text{DetM} \times D(\text{RandM}) \times [\text{Trace}] \times [\text{WhileMap}] \times \text{DB}) \rightarrow (\text{DetM} \times D(\text{RandM}) \times [\text{Trace}] \times [\text{WhileMap}] \times \text{DB})$. The upper case character T represents the list of traces and W represents the list of while map. The $@$ operator represents the list concatenation, and the $T.i$ represents the i^{th} element in the list T .

$$\langle (\sigma, \mu_1, T_1, W_1, D) \rangle \oplus_\rho \langle (\sigma, \mu_2, T_2, W_2, D) \rangle \triangleq \langle \sigma, \mu_1 \oplus_\rho \mu_2, T_1 @ T_2, W_1 @ W_2, D \rangle$$

$$T ++ t \triangleq [T.i ++ t]$$

$$W + l \triangleq [W.i + l]$$

$$W \setminus l \triangleq [W.i \setminus l]$$

$$\begin{aligned}
\llbracket [\text{skip}]^l \rrbracket (\sigma, \mu, T, W, D) &\triangleq (\sigma, \mu, T, W, D) \\
\llbracket [x \leftarrow e_d]^l \rrbracket (\sigma, \mu, T, W, D) &\triangleq (\sigma[x \rightarrow \llbracket e_d \rrbracket (\sigma)], \mu, T, W, D) \\
\llbracket [x_r \leftarrow e_r]^l \rrbracket (\sigma, \mu, T, W, D) &\triangleq (\sigma, \text{bind}(\mu, m \rightarrow \text{unit}(m[x_r \rightarrow \llbracket e_r \rrbracket (\sigma, m)])), T, W, D) \\
\llbracket [x \leftarrow q]^l \rrbracket (\sigma, \mu, T, W, D) &\triangleq (\sigma[x \rightarrow v], \mu, T + +[(q, v)]^{(l, W)}, W, D) \quad : v = q(D) \\
\llbracket [x_r \leftarrow \text{uniform}]^l \rrbracket (\sigma, \mu, T, W, D) &\triangleq (\sigma, \text{bind}(\mu, m \rightarrow \text{bind}(\text{uniform}, u \rightarrow m[x_r \rightarrow u])), T, W, D) \\
\llbracket [x_r \leftarrow \text{bernoulli}]^l \rrbracket (\sigma, \mu, T, W, D) &\triangleq (\sigma, \text{bind}(\mu, m \rightarrow \text{bind}(\text{bernoulli}, u \rightarrow m[x_r \rightarrow u])), T, W, D) \\
\llbracket [P; P'] \rrbracket (\sigma, \mu, T, W, D) &\triangleq \llbracket P' \rrbracket (\llbracket P \rrbracket \sigma, \mu, T, W) \\
\llbracket [\text{if}_D([b]^l, P_1, P_2)] \rrbracket (\sigma, \mu, T, W, D) &\triangleq \begin{cases} \llbracket P_1 \rrbracket (\sigma, \mu, T, W, D) & : \llbracket b \rrbracket (\sigma) = \text{true} \\ \llbracket P_2 \rrbracket (\sigma, \mu, T, W, D) & : \llbracket b \rrbracket (\sigma) = \text{false} \end{cases} \\
\llbracket [\text{if}_R([b]^l, P_1, P_2)] \rrbracket (\sigma, \mu, T, W, D) &\triangleq \begin{cases} \llbracket P_1 \rrbracket (\sigma, \mu | \llbracket b_r \rrbracket \sigma = \text{true}, T, W, D) \oplus_\rho \llbracket P_2 \rrbracket (\rho, \mu | \llbracket b_r \rrbracket \sigma = \text{false}, T, W, D) & \rho = 1 \\ \llbracket P_2 \rrbracket (\sigma, \mu | \llbracket b_r \rrbracket \sigma = \text{false}, T, W, D) & \rho = 0 \end{cases} \\
&\text{where } \rho = \mu(\llbracket b_r \rrbracket \sigma = \text{true}) \\
\llbracket [\text{while}([b]^l, P)] \rrbracket (\sigma, \mu, T, W, D) &\triangleq \llbracket [\text{unfold}([b]^l, \text{while}([b]^l, P))] \rrbracket (\sigma, \mu, T, W, D) \\
\llbracket [\text{unfold}([b]^l, P)] \rrbracket (\sigma, \mu, T, W, D) &\triangleq \begin{cases} \llbracket P \rrbracket (\sigma, \mu, T, W + l, D) & : \llbracket b \rrbracket (\sigma) = \text{true} \\ \llbracket [\text{skip}] \rrbracket (\sigma, \mu, T, W - l, D) & : \llbracket b \rrbracket (\sigma) = \text{false} \end{cases} \\
\llbracket [\text{switch}(e, x, (v_i \rightarrow q_i))]^l \rrbracket (\sigma, \mu, T, W, D) &\triangleq \llbracket [x \leftarrow q_1]^l \rrbracket (\sigma, \mu, T, W, D) \quad : v_1 = \llbracket e \rrbracket (\sigma) \\
\llbracket [\text{loop } [e_N]^l \text{ (f) do } P] \rrbracket (\sigma, \mu, T, W, D) &\triangleq \begin{cases} \llbracket [f; P; \text{loop } [e_N - 1]^l \text{ (f) do } P] \rrbracket (\sigma, \mu, T, W + l, D) & : \llbracket e_N \rrbracket (\sigma) > 0 \\ \llbracket [\text{skip}] \rrbracket (\sigma, \mu, T, W - l, D) & : \llbracket e_N \rrbracket (\sigma) = 0 \end{cases}
\end{aligned}$$

Figure 1: Semantics of programs

$$\begin{aligned}
&[j \leftarrow 0]^1; \\
&[I \leftarrow []]^2; \\
&\text{while}([j \leq k]^3, \\
&[p \leftarrow 0]^4; \\
&\left[\text{switch} \left(I, x \begin{pmatrix} [] \rightarrow q_{j,1}, \\ \dots \\ [1, 2, 3, \dots, n] \rightarrow q_{j,n!} \end{pmatrix} \right) \right]^5 \Rightarrow \text{SSA} \triangleq \left[\text{switch} \left(I_2, x \begin{pmatrix} [] \rightarrow q_{j,1}, \\ \dots \\ [1, 2, 3, \dots, n] \rightarrow q_{j,n!} \end{pmatrix} \right) \right]^5 \\
&[I \leftarrow \text{update}(I, (x, p))]^6; \\
&[j \leftarrow j + 1]^7); \\
&[j \leftarrow 0]^1; \\
&[I_1 \leftarrow []]^2; \\
&\text{while}([j \leq k]^3, \phi : I_2 = f(I_1, I_3) \\
&[p \leftarrow 0]^4; \\
&\left[\text{switch} \left(I_2, x \begin{pmatrix} [] \rightarrow q_{j,1}, \\ \dots \\ [1, 2, 3, \dots, n] \rightarrow q_{j,n!} \end{pmatrix} \right) \right]^5 \\
&[I_3 \leftarrow \text{update}(I_2, (x, p))]^6; \\
&[j \leftarrow j + 1]^7);
\end{aligned}$$

3.2 Extending Adaptivity onto Probabilistic Program

Definition 4. *Dependency Forest.*

Given a program P , a database D , dependency forest $F(P, D) \triangleq \{G_1, G_2, \dots, G_m\}$, $G_k = (V_k, E_k)$ is defined as:

$$\begin{aligned}
V_k &= \{q^{l,w} | \forall m, w. \langle \emptyset, P, D, [], \emptyset \rangle \rightarrow \langle m, \text{skip}, D, T, \emptyset \rangle \wedge q^{l,w} \in T.k\}; \\
E_k &= \{(q_i^{l,w}, q_j^{l',w'}) \mid \neg \text{IND}(q_i^{l,w}, q_j^{l',w'}, P) \wedge \text{To}(q_j^{l',w'}, q_i^{l,w})\},
\end{aligned}$$

Definition 5. *Dependency Graph.*

Given a program P , a database D , dependency graph $G(P, D) \triangleq (V, E)$ is defined as:

$$\begin{aligned}
V &= \bigcup \{V_k | G_k \in F(P, D)\}; \\
E &= \{(q_i, q_j) \mid (q_i, q_j) \in E_k, G_k \in F(P, D)\},
\end{aligned}$$

Definition 6. Adaptivity.

Given a program P and for all the database D in a set of DBS of databases, the total dependency graph G is the combination of all the dependent graphs over every single database $G(P, D) = (V, E)$, the adaptivity of the program is defined as $A(P)$, s.t.: for every pair (i, j) let $p_{(i,j)}$ be the longest path starting from $q_i^{l,w}$ to $q_j^{l',w'}$,

$$A(P) = \max_{q_i^{l,w}, q_j^{l',w'} \in V} \{l_i \mid l_i = |p_{(i,j)}|\}$$

4 Analysis of Program Adaptivity

We have the analysis rules of the form $\vdash_{M,V}^{i_1, i_2} C$. Our grade is a combination of a matrix M , used to track the dependency of variables appeared in the statement S , and a vector V indicating the variables associated with results from queries q . The size of the matrix M is $L \times L$, and vector V of size N , where L is the total size of variables needed in the program, which is fixed per program. The superscript i_1, i_2 is a counter specifying the range of "living" or "active" variables in the matrix and vector. i_1 is the starting line (and column) in the matrix where the new generated variables in program P starts to show up. Likewise, i_2 states the ending position of active range by C . The new generated variables will be treated carefully when we handle recursive statement, in our case, the loop statement.

We assume the program C is in the static single assignment form. That is to say, $x \leftarrow e_1; x \leftarrow e_2$ will be rewritten as $x_1 \leftarrow e_1; x_2 \leftarrow e_2$. And the if condition `if e_b then $x \leftarrow e_1$ else $x \leftarrow e_2$` will look like `if e_b then $x_1 \leftarrow e_1$ else $x_2 \leftarrow e_2$` . As we have seen, ssa provides unique variables, and these newly generated variables will be recorded in the matrix M . Worth to mention, i_1, i_2 can be used to track the exact location of newly generated variables. For example, the assignment statement $x \leftarrow e$ or $x \leftarrow q$ holds $i_2 = i_1 + 1$, telling us the variable x is at the i_1 th line(column) of the matrix. As we can notice, the loop increases the matrix by $N \times a$ where N is the number of rounds of the loop and a is the size of the variables generated in the loop body C .

We will have a global map, which maps the variable name to the position in the vector. We call it $G: VAR \rightarrow \mathbb{N}$,

We give an example of M and V of the program C .

$$P = \begin{array}{l} x_1 \leftarrow q; \\ x_2 \leftarrow x_1 + 1; \\ x_3 \leftarrow x_2 + 2 \end{array} \quad M = \begin{array}{cccc} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \end{array}, V = \begin{array}{c} 0 \\ 0 \\ 0 \end{array}$$

Analysis Rules.

$$\begin{array}{ll} \text{Predict}(x \leftarrow e)(\Gamma, i) & = (L(x) * (R(e) + \Gamma), V, i + 1) \\ \text{Predict}(x \leftarrow q)(\Gamma, i) & = (L(x) * (R(\emptyset) + \Gamma), L(x), i + 1) \\ \text{Predict}(\text{if } e_b \text{ then } C_1 \text{ else } C_2)(\Gamma, i) & = \text{let } (M_1, v_1, i_1) = \text{Predict}(C_1)(\Gamma + R(e_b), i) \text{ in} \\ & \quad \text{let } (M_2, v_2, i_2) = \text{Predict}(C_2)(\Gamma + R(e_b), i_1) \text{ in } (M_1 \uplus M_2, V_1 \uplus V_2, i_2) \\ \text{Predict}(C_1; C_2)(\Gamma, i) & = \text{let } (M_1, v_1, i_1) = \text{Predict}(C_1)(\Gamma + R(e_b), i) \text{ in} \\ & \quad \text{let } (M_2, v_2, i_2) = \text{Predict}(C_2)(\Gamma + R(e_b), i_1) \text{ in } (M_1 \cdot M_2, V_1 \uplus V_2, i_2) \end{array}$$

Analysis Logic Rules.

$$\boxed{\Gamma \vdash_{M,V}^{c_1, c_2} P : \Phi \Rightarrow \Psi}$$

$$\frac{M = L(x) * (R(e) + \Gamma)}{\Gamma \vdash_{M, V_\emptyset}^{(c, c+1)} x \leftarrow e : \Phi \Rightarrow \Psi}$$

$$\frac{M = L(x) * (R(\emptyset) + \Gamma) \quad V = L(x)}{\Gamma \vdash_{M, V}^{(c, c+1)} x \leftarrow q : \Phi \Rightarrow \Psi}$$

$$\frac{\Gamma + R(e_b) \vdash_{M_1, V_1}^{(c_1, c_2)} P_1 : \Phi \Rightarrow \Psi \quad \Gamma + R(e_b) \vdash_{M_2, V_2}^{(c_2, c_3)} P_2 : \Phi \Rightarrow \Psi}{\Gamma \vdash_{M_1 \uplus M_2, V_1 \uplus V_2}^{(c_1, c_3)} \text{if } e_b \text{ then } P_1 \text{ else } P_2 : \Phi \Rightarrow \Psi}$$

$$\frac{\Gamma \vdash_{M_1, V_1}^{(c_1, c_2)} P_1 : \Phi \Rightarrow \Psi' \quad \Gamma \vdash_{M_2, V_2}^{(c_2, c_3)} P_2 : \Psi' \Rightarrow \Psi}{\Gamma \vdash_{M_1 \cdot M_2, V_1 \uplus V_2}^{(c_1, c_3)} P_1; P_2 : \Phi \Rightarrow \Psi}$$

$$\frac{\forall 0 \leq z < N. \Gamma \vdash_{M, V}^{(c, c+a)} f; P : \{\Phi \wedge e_N = z + 1\} \Rightarrow \{\Phi \wedge e_N = z\}}{\Gamma \vdash_{M_{c,a}^N(f), V_{c,a}^N}^{(c, c+N*a)} \text{loop } e_N (f) \text{ do } P : \{\Phi \wedge e_N = N\} \Rightarrow \{\Phi \wedge e_N = 0\}}$$

$$\frac{\Gamma + R(e) \vdash_{M_i, V_i}^{(c_1, c_1+1)} x_i \leftarrow q_i \quad i \in \{1, \dots, N\}}{\Gamma \vdash_{\sum_{i=0}^N M_i, \sum_{i=0}^N V_i}^{(c_1, c_1+N)} \text{switch}(e, x, (v_i \rightarrow q_i))}$$

$$V_1 \uplus V_2 := \begin{cases} 1 & (V_1[i] = 1 \vee V_2[i] = 1) \wedge i = 1, \dots, N \wedge |V_1| = |V_2| \\ 0 & o.w. \end{cases}$$

$$M_1 \uplus M_2 := \begin{cases} 1 & (M_1[i][j] = 1 \vee M_2[i][j] = 1) \wedge i, j = 1, \dots, N \wedge |M_1| = |M_2| \\ 0 & (M_1[i][j] = 0 \wedge M_2[i, j] = 0) \wedge i, j = 1, \dots, N \wedge |M_1| = |M_2| \\ \perp & o.w. \end{cases}$$

$$V_{(c,a)}^N := \begin{cases} V[c + i * a, c + (i + 1) * a - 1] = V[c, c + a - 1] & i = 1, \dots, N - 1 \\ \perp & o.w. \end{cases}$$

$$M_{(c,a)}^N(f) := \begin{cases} M[c + i * a, c + (i + 1) * a - 1][c + i * a, c + (i + 1) * a - 1] \\ = M[c, c + a - 1][c, c + a - 1] & i = 1, \dots, N - 1 \\ M[c + i * a, c + (i + 1) * a - 1][0, c + (i) * a - 1] = 0 & i = 1, \dots, N - 1 \\ M[0, c + i * a - 1][c + i * a, c + (i + 1) * a - 1] \\ = M[0, c + (i - 1) * a - 1][c + (i - 1) * a, c + (i) * a - 1] & i = 1, \dots, N - 1 \\ M[l][k] = 1 & l \in [c + (i - 1) * a, c + (i) * a - 1], \\ & k \in [c + i * a, c + (i + 1) * a - 1] \\ & \wedge i = 1, \dots, N \wedge, l = G(x_l) \\ & \wedge k = G(x_k) \wedge x_l = f(\dots, x_k, \dots) \\ \perp & o.w. \end{cases}$$

1	...	c-1	c	...	c+a-1	c+a	...	c+2a-1	...	c+N*a-1	c+N*a	...
...			0	0	0	0	0	0				
c-1			0	0	0	0	0	0				
c						0	0	0				
...						0	0	0				
c+a-1						0	0	0				
c+a												
...				f								
c+2a-1												
...												
c+N*a-1												
c+N*a												
...												

Definition 7. *Dependency Graph.*

Given a program P , a database D , dependency graph $G(P, D) = (V, E)$ is defined as:

$$V = \{q_i^{l,w} \mid \forall \sigma, \sigma', \mu, \mu', w, w', t, t'. \llbracket P \rrbracket(\sigma, \mu, t, w, D) \triangleq (\sigma', \mu', t', w', D) \wedge q_i^{l,w} \in (t' - t)\}.$$

$$E = \{(q_i^{l,w}, q_j^{l',w'}) \mid \neg \text{IND}(q_i^{l,w}, q_j^{l',w'}, P) \wedge \text{To}(q_j^{l',w'}, q_i^{l,w})\}.$$

Definition 8. Two queries q_i and q_j in a program c are independent, $\text{IND}(q_i^{l_1}, q_j^{l_2}, P)$.

$$\begin{aligned} & \forall m, D. (\llbracket P \rrbracket(\sigma, \mu, \mathbf{t}, w, D) \triangleq (\sigma', \mu', t', w', D) \\ & \wedge ((q_i^{l_1}, v_i) \in t' \wedge (q_j^{l_2}, v_j) \in t' \implies \forall v \in \text{Codom}(q_i^{l_1}). (\llbracket P[v/q_i] \rrbracket(\sigma, \mu, \mathbf{t}, w, D) \triangleq (\sigma', \mu', t'', w', D) \wedge (q_j^{l_2}, v_j) \in t'')) \\ & \wedge ((q_i^{l_1}, v_i) \in t \wedge (q_j^{l_2}, v_j) \notin t \implies \forall v \in \text{Codom}(q_i^{l_1}). (\llbracket P[v/q_i] \rrbracket(\sigma, \mu, \mathbf{t}, w, D) \triangleq (\sigma', \mu', t'', w', D) \wedge (q_j^{l_2}, v_j) \notin t''))). \end{aligned}$$

Definition 9. *Adaptivity.*

Given a program P and for all the database D in a set of DBS of databases, the total dependency graph G is the combination of all the dependent graphs over every single database $G(P, D) = (V, E)$, the adaptivity of the program is defined as $A(P)$, s.t.: for every pair (i, j) let $p_{(i,j)}$ be the longest path starting from $q_i^{l,w}$ to $q_j^{l',w'}$,

$$A(P) = \max_{q_i^{l,w}, q_j^{l',w'} \in V} \{l_i \mid l_i = |p(i, j)|\}$$

Definition 10 (Adapt). Given a program P s.t. $\cdot \vdash_{M,V}^{c_1, c_2} P : \Phi \implies \Psi$, there exists 1 and only one Graph $G(M, V) = (\text{Nodes}, \text{Edges}, \text{Weights})$ defined as:

$$\text{Nodes} = \{i \mid i \in V\}$$

$$\text{Edges} = \{(i, j) \mid M[i][j] \geq 1\}$$

$Weights = \{1 | i \in V \wedge V[i] = 1\} \cup \{-1 | i \in V \wedge V[i] = 0\}$

Adaptivity of the program defined according to the logic is as:

$$Adapt(M, V) := \max_{k, l \in Nodes} \{i | V[i] = 1 \wedge i \in p(k, l)\},$$

where $p(k, l)$ is the longest weighted path in graph $G(M, V)$ starting from k to l .

Definition 11 (Subgraph). Given two graphs $G_1 = (V_1, E_1)$, $G_2 = (V_2, E_2)$, $G_1 \subseteq G_2$ iff:

1. $V_1 \subseteq V_2$;
2. $\forall (q_i, q_j) \in E_1, \exists$ a path in G_2 from q_i to q_j .

Theorem 4.1 (Soundness). Given a program P , Γ , μ , c_1, c_2 and σ s.t. $FreeVar(P) \subseteq dom(\sigma) \cup dom(\mu) \wedge \Gamma \vdash_{M, V}^{c_1, c_2} P : \Phi \implies \Psi$, for all database D , $(\sigma, \mu) \models t$ s.t. $\llbracket P \rrbracket(\sigma, \mu, t, w, D) \triangleq (\sigma', \mu', t', w', D)$, then

$$A(P) \leq Adapt(M, V)$$

Proof. By induction on the judgment $\Gamma \vdash_{M, V}^{c_1, c_2} P : \Phi \implies \Psi$.

- **Case:**
$$\frac{M = L(x) * (R(e) + \Gamma)}{\Gamma \vdash_{M, V_\emptyset}^{(c, c+1)} x \leftarrow e : \Phi \implies \Psi}$$

Given σ , μ , t and w , for arbitrary database D , by induction on e , we have the following semantic.

$$\llbracket [x \leftarrow e_d]^l \rrbracket(\sigma, \mu, t, w, D) \triangleq (\sigma[x \rightarrow \llbracket e_d \rrbracket(\sigma), \mu, t, w, D)$$

$$\llbracket [x_r \leftarrow e_r]^l \rrbracket(\sigma, \mu, t, w, D) \triangleq (\sigma, bind(\mu, m \rightarrow unit(m[x_r \rightarrow \llbracket e_r \rrbracket(\sigma, m)])), t, w, D)$$

In both of the 2 cases, no newly added node in the trace t . Then we can derive that $A(P) = 0$.

We also know $V_\emptyset = \emptyset$, i.e., $Adapt(M, V_\emptyset) = 0$.

Since $0 \leq 0$, this case is proved.

- **Case:**
$$\frac{M = L(x) * (R(\emptyset) + \Gamma) \quad V = L(x)}{\Gamma \vdash_{M, V}^{(c, c+1)} x \leftarrow q : \Phi \implies \Psi}$$

Given σ , μ , t and w , for arbitrary database D , we have the following semantic.

$$\llbracket [x \leftarrow q]^l \rrbracket(\sigma, \mu, t, w, D) \triangleq (\sigma[x \rightarrow v], \mu, t + [(q, v)]^{(l, w)}, w, D) \quad : v = q(D)$$

There is only one newly added node in the trace for all the possible database D . Follow the definition of $Adapt(M, V)$, we know that the claim holds.

- **Case:**
$$\frac{\Gamma + R(e_b) \vdash_{M_1, V_1}^{(c_1, c_2)} P_1 : \Phi \implies \Psi \quad \Gamma + R(e_b) \vdash_{M_2, V_2}^{(c_2, c_3)} P_2 : \Phi \implies \Psi}{\Gamma \vdash_{M_1 \uplus M_2, V_1 \uplus V_2}^{(c_1, c_3)} \text{if } e_b \text{ then } P_1 \text{ else } P_2 : \Phi \implies \Psi}$$

The semantics depends on the evaluated value of the conditional.

$$\llbracket \text{if}_D([b]^l, P_1, P_2) \rrbracket(\sigma, \mu, t, w, D) \triangleq \begin{cases} \llbracket P_1 \rrbracket(\sigma, \mu, t, w, D) & : \llbracket b \rrbracket(\sigma) = \text{true} \\ \llbracket P_2 \rrbracket(\sigma, \mu, t, w, D) & : \llbracket b \rrbracket(\sigma) = \text{false} \end{cases}$$

By induction hypothesis, we have:

$$A(P_1) \leq Adapt(M_1, V_1)$$

$$A(P_2) \leq Adapt(M_2, V_2)$$

By definition of $A(P)$ and $Adapt(M, V)$, we have:

$$A(P) \leq \max(A(P_1), A(P_2)) \leq \max(Adapt(M_1, V_1), Adapt(M_2, V_2)) \leq Adapt(M_1 \uplus M_2, V_1 \uplus V_2).$$

This case is proved.

$$\bullet \text{ Case: } \frac{\Gamma \vdash_{M_1, V_1}^{(c_1, c_2)} P_1 : \Phi \Rightarrow \Psi' \quad \Gamma \vdash_{M_2, V_2}^{(c_2, c_3)} P_2 : \Psi' \Rightarrow \Psi}{\Gamma \vdash_{M_1 \cdot M_2, V_1 \uplus V_2}^{(c_1, c_3)} P_1; P_2 : \Phi \Rightarrow \Psi}$$

Given σ, μ, t and w , for arbitrary database D , we have the following semantic.

$$\llbracket P_1; P_2 \rrbracket(\sigma, \mu, t, w, D) \triangleq \llbracket P_2 \rrbracket(\llbracket P_1 \rrbracket(\sigma, \mu, t, w, D))$$

Let $\llbracket P_1 \rrbracket(\sigma, \mu, t, w, D) = (\sigma_1, \mu_1, t_1, w_2, D)$, $\llbracket P_2 \rrbracket(\llbracket P_1 \rrbracket(\sigma, \mu, t, w, D)) = (\sigma_2, \mu_2, t_2, w_2, D)$.

The goal is to show: $A(P_1; P_2) \leq \text{Adapt}(M_1 \cdot M_2, V_1 \uplus V_2)$

By induction hypothesis, we have: $A(P_1) \leq \text{Adapt}(M_1, V_1)$ and $A(P_2) \leq \text{Adapt}(M_2, V_2)$.

By definition of V and t , we know the newly added queries in t_2 compared to the original trace t must be the same as newly added queries marked in $V_1 \uplus V_2$, i.e., the query nodes in the dependency graph must be contained in the Adapt graph generated by $M_1 \cdot M_2, V_1 \uplus V_2$.

On the other hand, any dependency between newly added queries in $t_2 - t$ is tracked by $M_1 \cdot M_2$. It is shown in 3 cases: (1) dependency between queries nodes in P_1 is recorded in M_1 . (2) dependency between queries nodes in P_2 is recorded in M_2 . (3) dependency between query nodes from P_1 and P_2 respectively is tracked by $M_2 \times M_1$. To sum up, the dependency relation must be contained in $M_1 \cdot M_2$.

Then we can conclude in this case, the longest path in the dependency graph of $P_1; P_2$ must be contained in the Adapt graph generated by $M_1 \cdot M_2, V_1 \uplus V_2$, i.e., $A(P_1; P_2) \leq \text{Adapt}(M_1 \cdot M_2, V_1 \uplus V_2)$.

This case is proved.

$$\bullet \text{ Case: } \frac{\Gamma + R(e) \vdash_{M_i, V_i}^{(c_1, c_1+1)} x_i \leftarrow q_i \quad i \in \{1, \dots, N\}}{\Gamma \vdash_{\sum_{i=0}^N M_i, \sum_{i=0}^N V_i}^{(c_1, c_1+N)} \text{switch}(e, x, (v_i \rightarrow q_i))}$$

Given σ, μ, t and w , for arbitrary database D , we have the following semantic.

$$\llbracket [\text{switch}(e, x, (v_i \rightarrow q_i))]^l \rrbracket(\sigma, \mu, t, w, D) \triangleq \llbracket [x \leftarrow q_1]^l \rrbracket(\sigma, \mu, t, w, D) \quad : v_1 = \llbracket e \rrbracket(\sigma)$$

Let $\llbracket [x \leftarrow q_1]^l \rrbracket(\sigma, \mu, t, w, D) = (\sigma[x \rightarrow v'_1], \mu, t + [(v_1, q_1)], w, D)$.

We then have: $\llbracket [\text{switch}(e, x, (v_i \rightarrow q_i))]^l \rrbracket(\sigma, \mu, t, w, D) = (\sigma[x \rightarrow v'_1], \mu, t + [(v_1, q_1)], w, D)$

The goal is to show: $A([\text{switch}(e, x, (v_i \rightarrow q_i))]^l) \leq \text{Adapt}(\sum_{i=0}^N M_i, \sum_{i=0}^N V_i)$

By induction hypothesis, we have: $A([x \leftarrow q_i]^l) \leq \text{Adapt}(M_i, V_i)$ for any $v_i = q_i$.

Then we have $A([\text{switch}(e, x, (v_i \rightarrow q_i))]^l) \leq \text{Adapt}(M_i, V_i)$ for any $v_i = q_i$.

Since we also have: $\text{Adapt}(M_i, V_i) \leq \text{Adapt}(\sum_{i=0}^N M_i, \sum_{i=0}^N V_i)$ for any $v_i = q_i$, this case is proved.

$$\bullet \text{ Case: } \frac{\Gamma \vdash_{M, V}^{(c, c+a)} f; P : \{\Phi \wedge e_N = z + 1\} \Rightarrow \{\Phi \wedge e_N = z\}}{\Gamma \vdash_{M_{c,a}^N(f), V_{c,a}^N}^{(c, c+N*a)} \text{loop } e_N(f) \text{ do } P : \{\Phi \wedge e_N = N\} \Rightarrow \{\Phi \wedge e_N = 0\}}$$

Given σ, μ, t and w , for arbitrary database D , we have the following semantic.

$$\llbracket \text{loop } [e_N]^l(f) \text{ do } P \rrbracket(\sigma, \mu, t, w, D) \triangleq \begin{cases} \llbracket f; P; \text{loop } [e_N - 1]^l(f) \text{ do } P \rrbracket(\sigma, \mu, t, w + l, D) & : \llbracket e_N \rrbracket(\sigma) > 0 \\ \llbracket \text{skip} \rrbracket(\sigma, \mu, t, w - l, D) & : \llbracket e_N \rrbracket(\sigma) = 0 \end{cases}$$

By induction on $\llbracket e_N \rrbracket(\sigma)$, we have sub-cases of $\llbracket e_N \rrbracket(\sigma) = 0$ and $\llbracket e_N \rrbracket(\sigma) > 0$.

Sub-case of $\llbracket e_N \rrbracket(\sigma) = 0$ is obviously true.

Sub-case of $\llbracket e_N \rrbracket(\sigma) > 0$:

The goal is to prove $A(f; P; \text{loop } [e_N - 1]^l(f) \text{ do } P) \leq \text{Adapt}(M_{c,a}^N(f), V_{c,a})$.

By unfolding the semantics of sequence, we have:

$$\llbracket f; P; \text{loop } [e_N - 1]^l (f) \text{ do } P \rrbracket (\sigma, \mu, t, w + l, D) = \llbracket \text{loop } [e_N - 1]^l (f) \text{ do } P \rrbracket (\llbracket f; P \rrbracket (\sigma, \mu, t, w + l, D)).$$

By induction hypothesis, we have: $A(f; P) \leq \text{Adapt}(M, V)$.

Let $\llbracket f; P \rrbracket (\sigma, \mu, t, w + l, D) = (\sigma_1, \mu_1, t_1, w_1, D)$. By Lemma 1(Subgraph), we know

- (a). the newly added queries in t_1 must be contained in the queries nodes in V ,
- (b). the dependency between newly added queries must be contained in M .

Let $\llbracket \text{loop } [e_N - 1]^l (f) \text{ do } P \rrbracket (\sigma_1, \mu_1, t_1, w_1, D) = (\sigma_N, \mu_N, t_N, w_{Nl}, D)$, by definition of $V_{(c,a)}^N$ and $M_{(c,a)}^N(f)$ and (a) and (b), we have:

- (1). All newly added queries in t_N must be contained in the queries nodes in $V_{(c,a)}^N$, this is proved jointly by (a).
- (2). All the dependency between queries internally in P for all the N rounds are contained in $M_{(c,a)}^N(f)$ according to its definition case 1, this is proved jointly by (b).
- (3). For all the dependency between queries in different rounds (for example, one query in the second iteration depending on the result of another query in the first iteration), they are recorded in f , which is also contained in $M_{(c,a)}^N(f)$ according to its definition case 3.
- (4) For all the dependency between queries in P and outside P , since the newly added queries are all comes from P , we don't consider the adaptivity outside the scope of program.

According to (1) - (4), we can conclude in this case, the longest path in the dependency graph of $P; \text{loop } [e_N - 1]^l (f) \text{ do } P$ must be contained in the Adapt graph generated by $M_{(c,a)}^N(f), V_{(c,a)}^N$, i.e., $A(P; \text{loop } [e_N - 1]^l (f) \text{ do } P) \leq \text{Adapt}(M_{(c,a)}^N(f), V_{(c,a)}^N)$.

This case is proved.

□

Lemma 1 (Subgraph). *Given a program P, Γ, μ, c_1, c_2 and σ s.t. $\text{FreeVar}(P) \subseteq \text{dom}(\sigma) \cup \text{dom}(\mu) \wedge \Gamma \subseteq \text{FreeVar}(P) \wedge \Gamma \vdash_{M,V}^{c_1, c_2} P : \Phi \implies \Psi$, for all database $D, (\sigma, \mu) \models t$ s.t. $\llbracket P \rrbracket (\sigma, \mu, t, w, D) \triangleq (\sigma', \mu', t', w', D)$, then*

$$G(P, D) \subseteq G(M, V)$$