

Scaling Abstraction Refinement via Pruning

PLDI - San Jose, CA

June 8, 2011

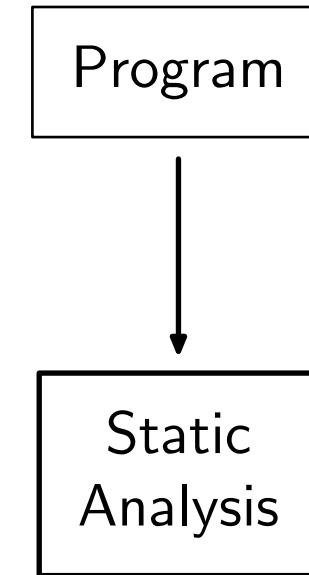
Percy Liang
UC Berkeley

Mayur Naik
Intel Labs Berkeley

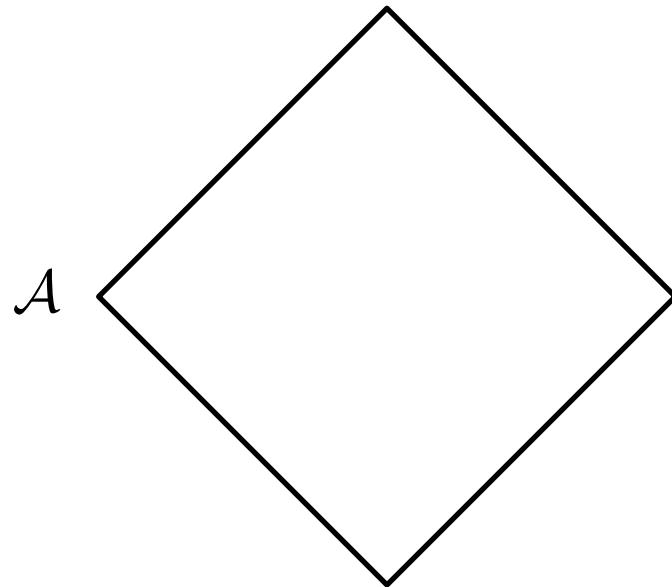
The Big Picture

Program

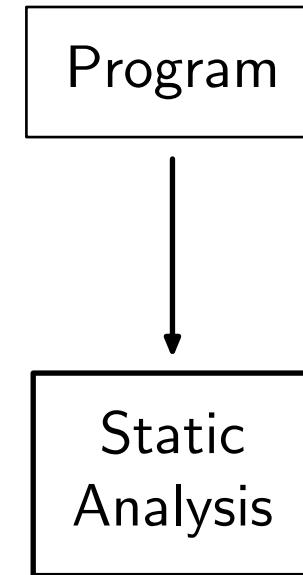
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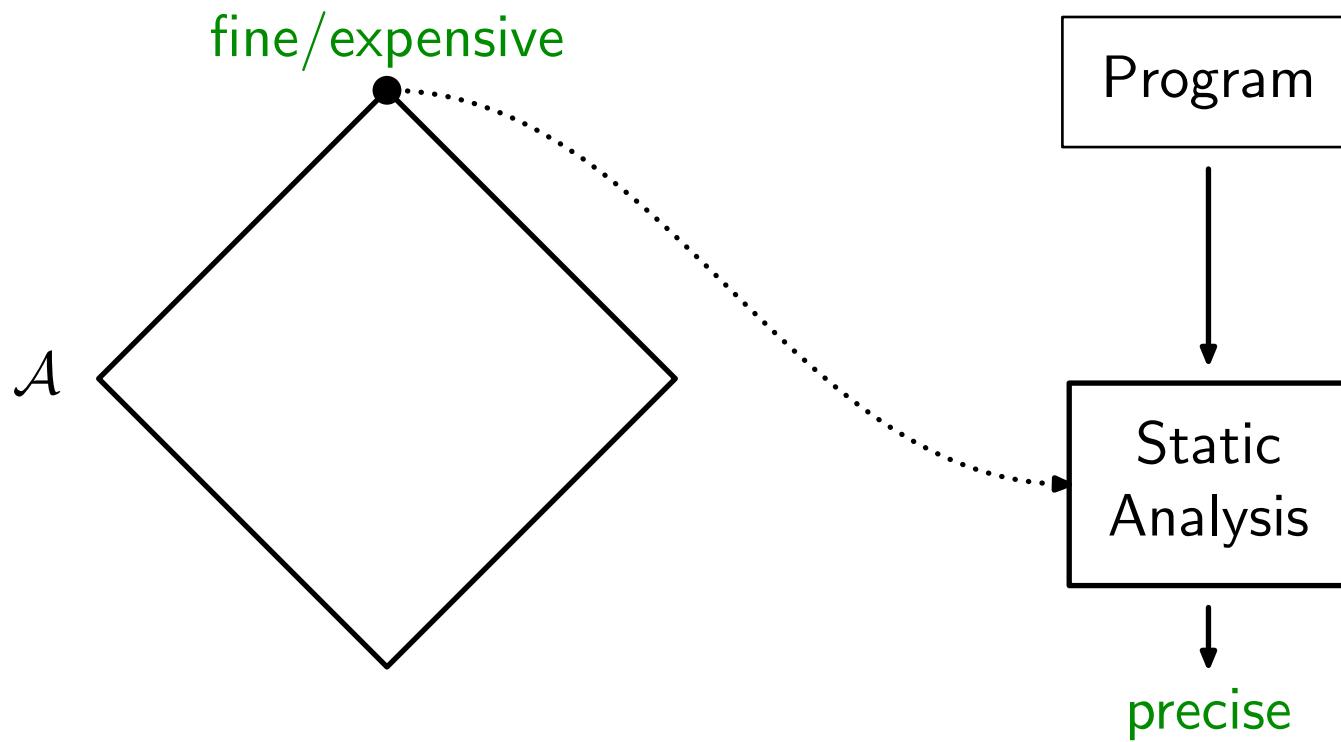
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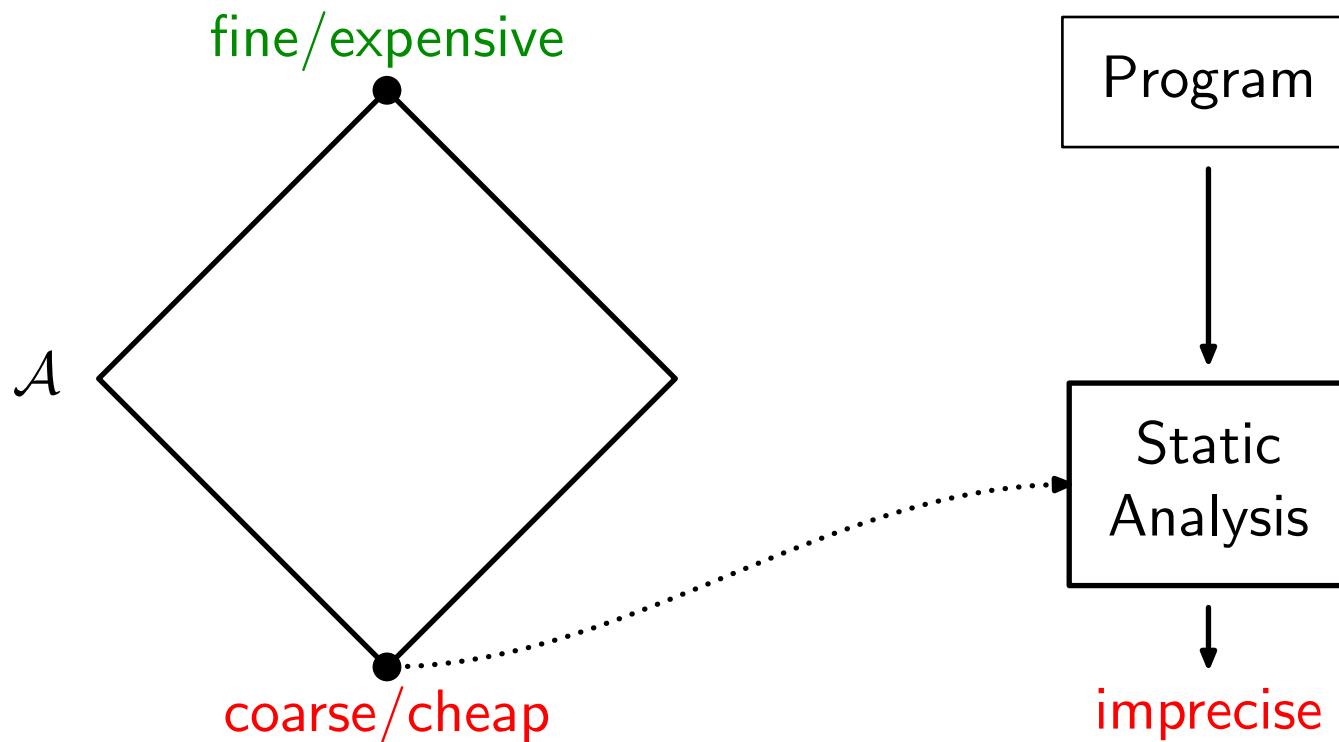
\mathcal{A}



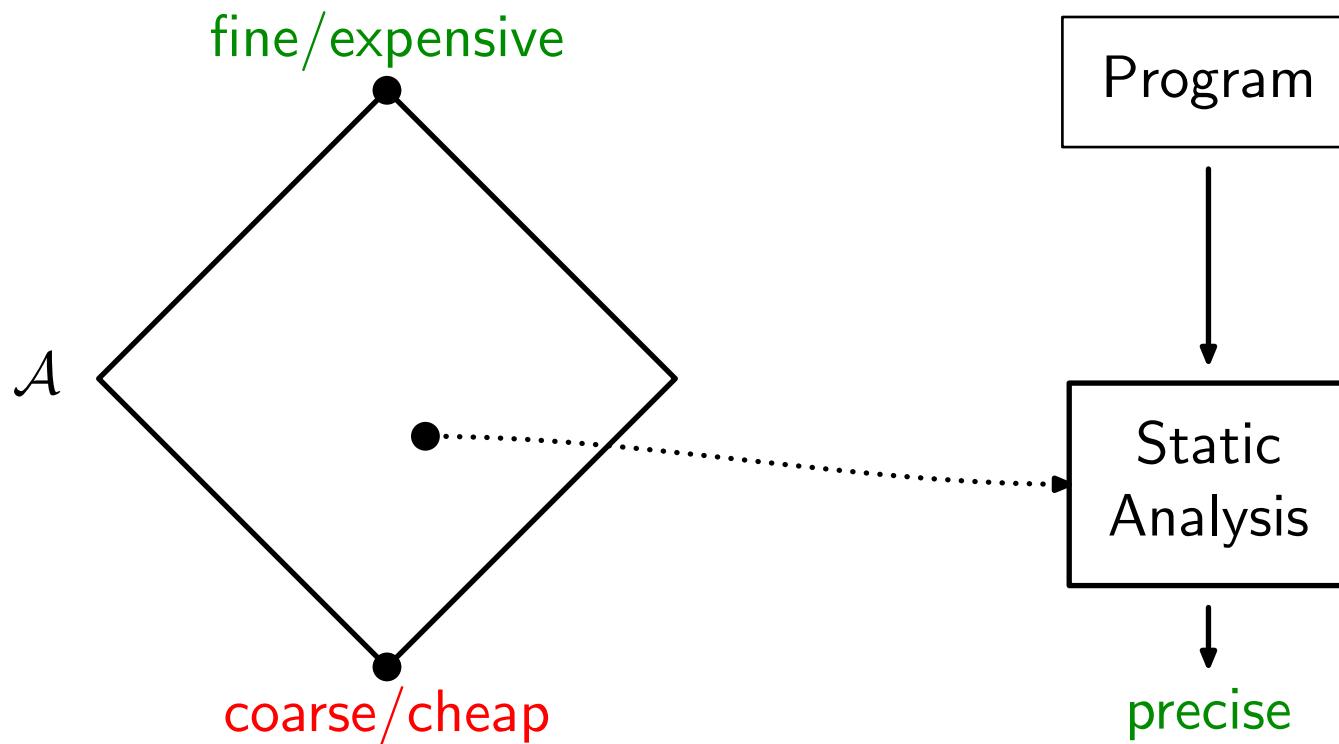
The Big Picture



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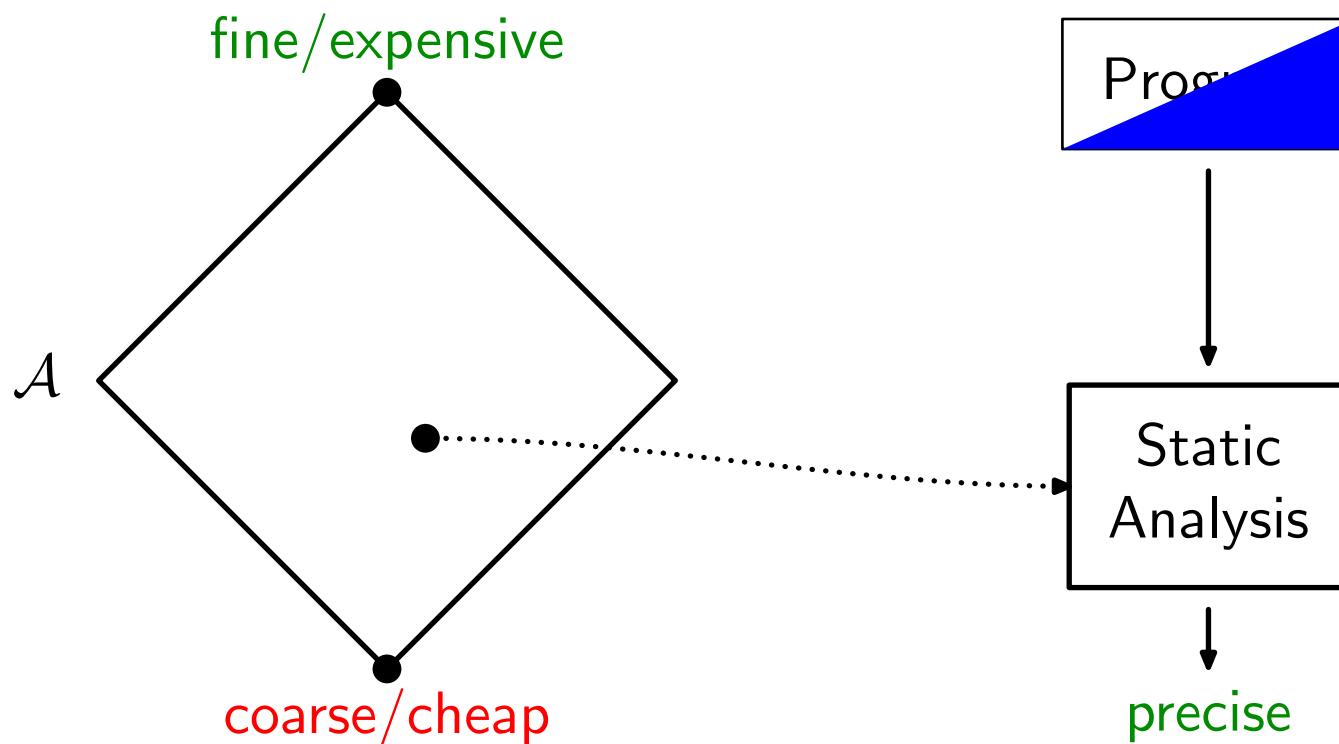
The Big Picture



selected refinement

- [Heintze & Tardieu 2001]
- [Guyer & Lin 2003]
- [Sridharan et al. 2005]
- [Zheng & Rugina 2008]
- [Liang et al. 2011]

The Big Picture



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pruning

NEW!

An Example of Pruning

```
getnew() {  
h1:    u = new C  
h2:    v = new C  
       return v  
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v = new C

x = getnew()

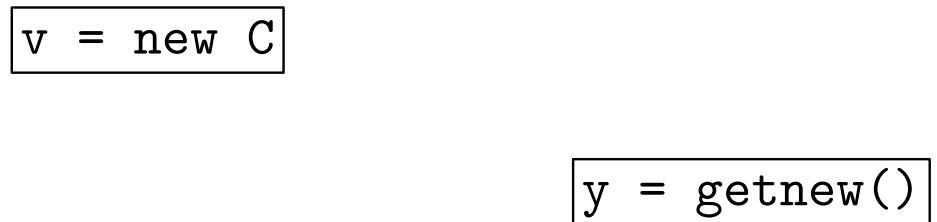
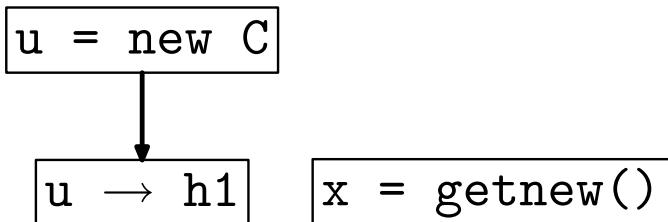
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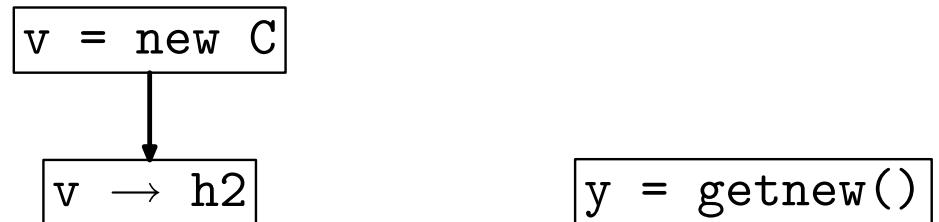
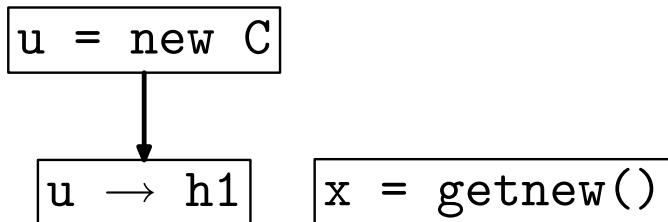


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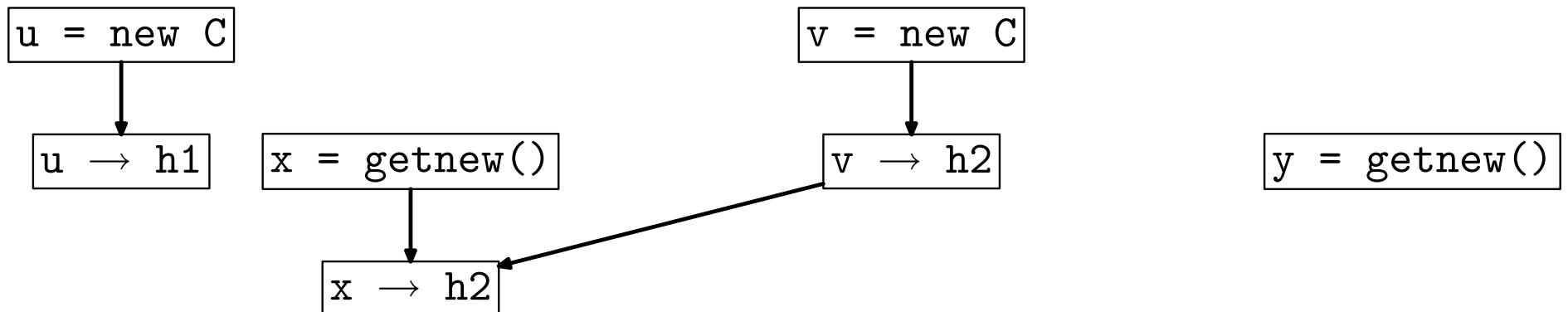


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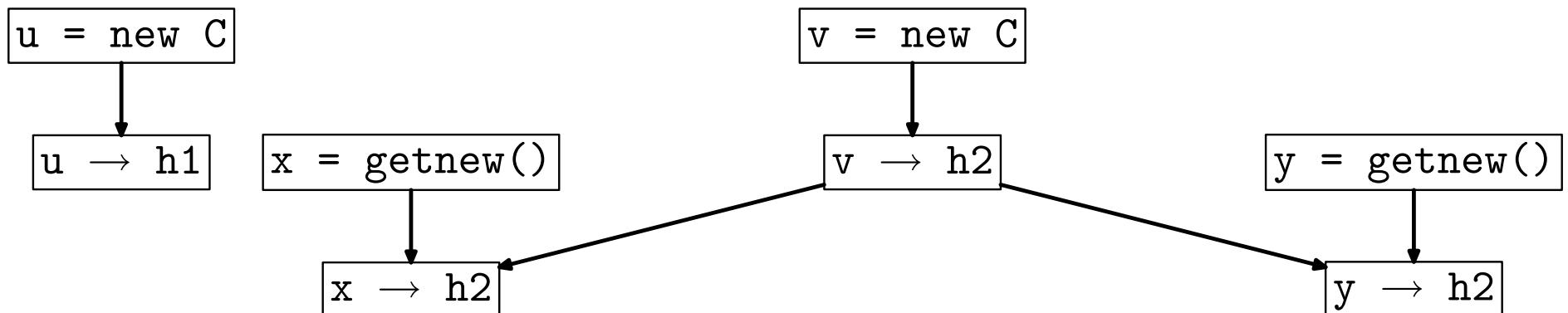


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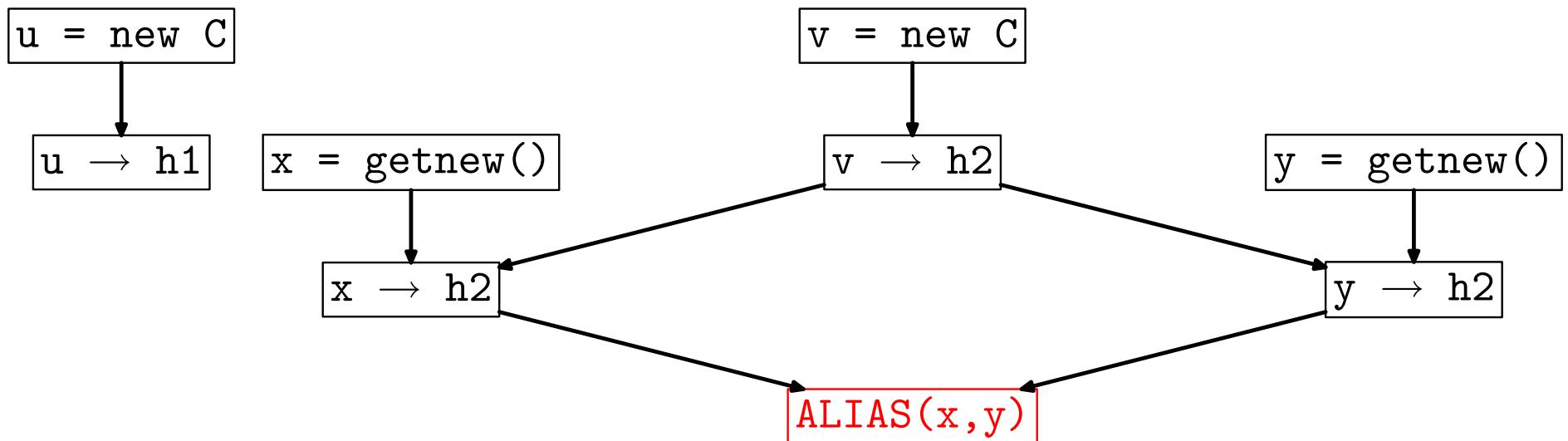


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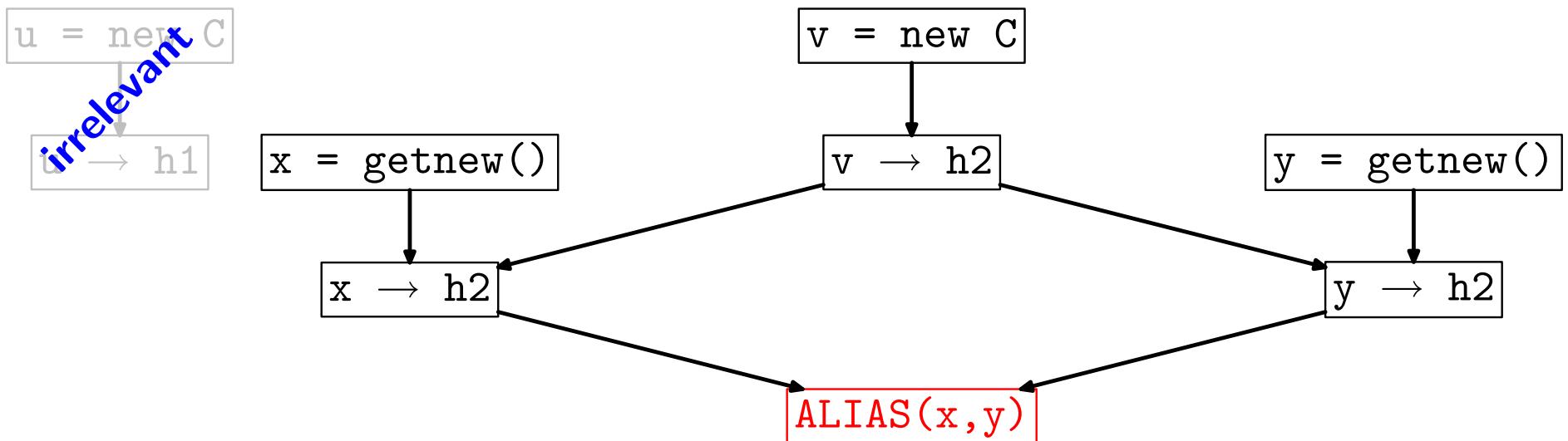


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1-CFA on pruned:

u = new C

irrelevant
u → h1

v:i1 = new C v:i2 = new C

x = getnew()

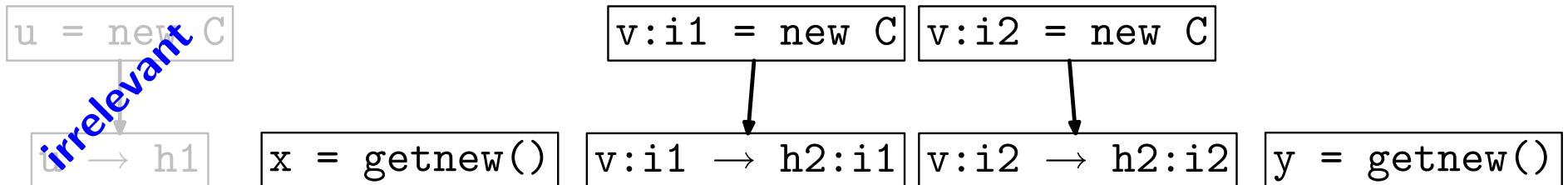
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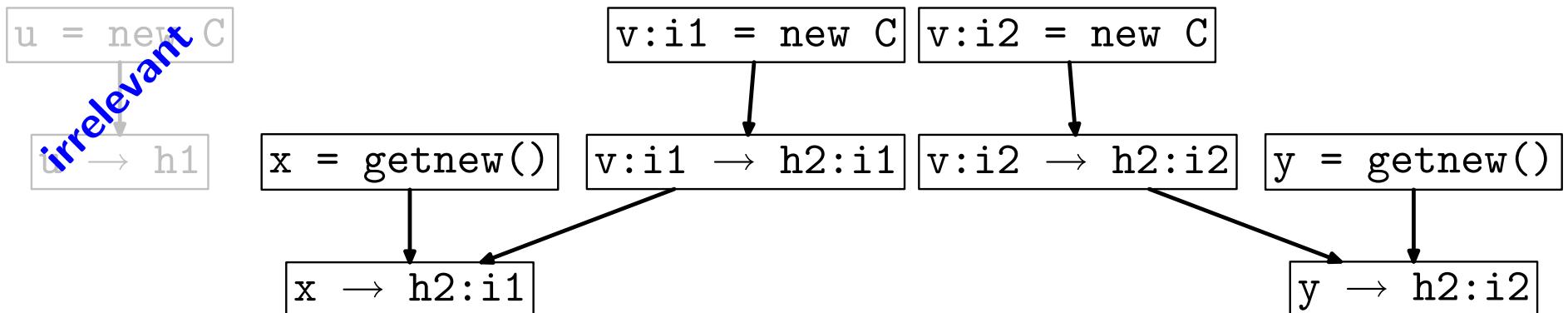


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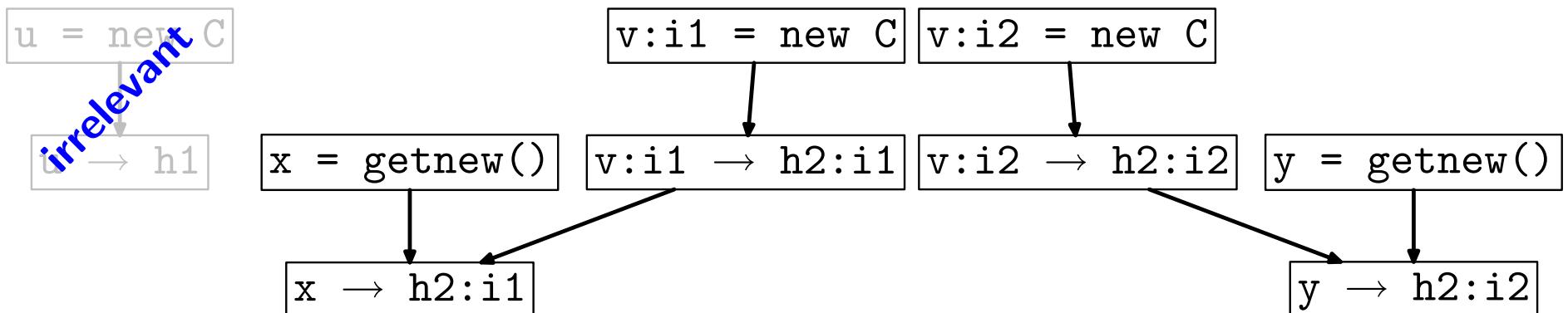


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(not aliasing - query proven)

General Pruning Framework

Input tuples A_0

```
v = new C ...
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Query tuple x_Q

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ALIAS(x,y)
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Datalog rules

$v_2 \rightarrow h \Leftarrow v_2 = v_1, v_1 \rightarrow h$

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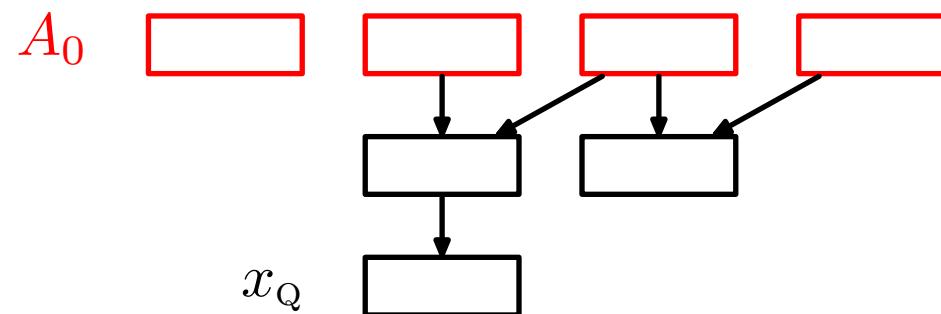
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Prune/prove operator P

$A_0 \xrightarrow{P}$ subset of A_0 used to derive x_Q



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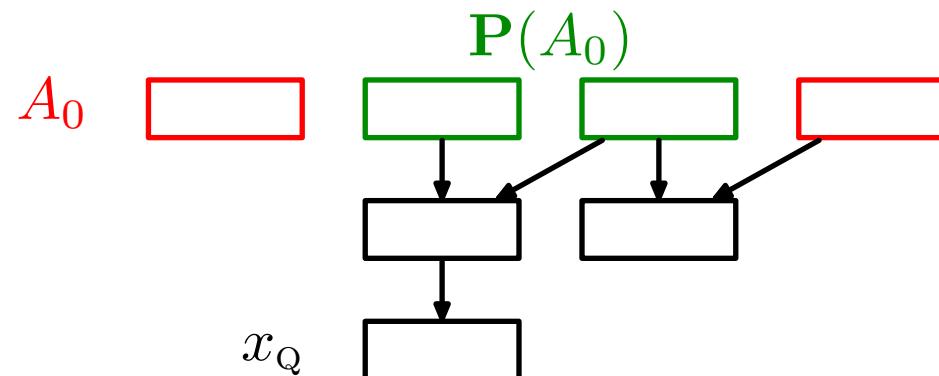
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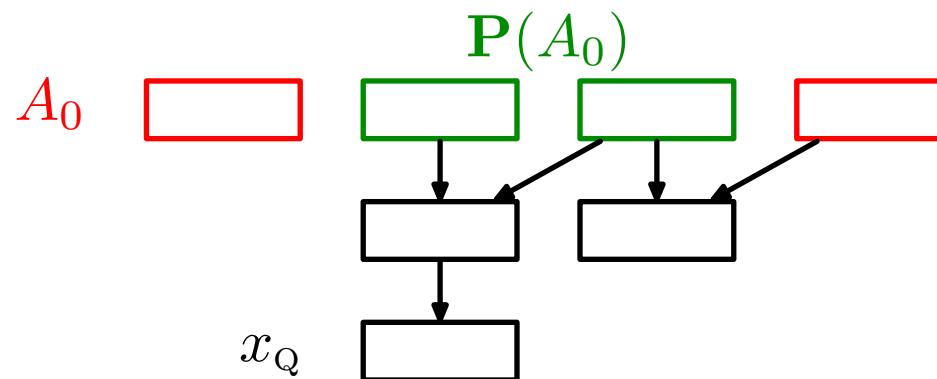
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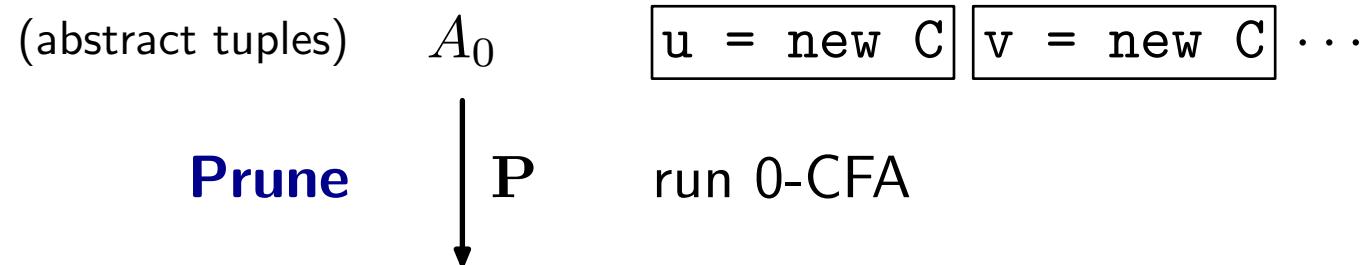
Query proven $\Leftrightarrow \mathbf{P}(A_0) = \emptyset$

Prune and Refine

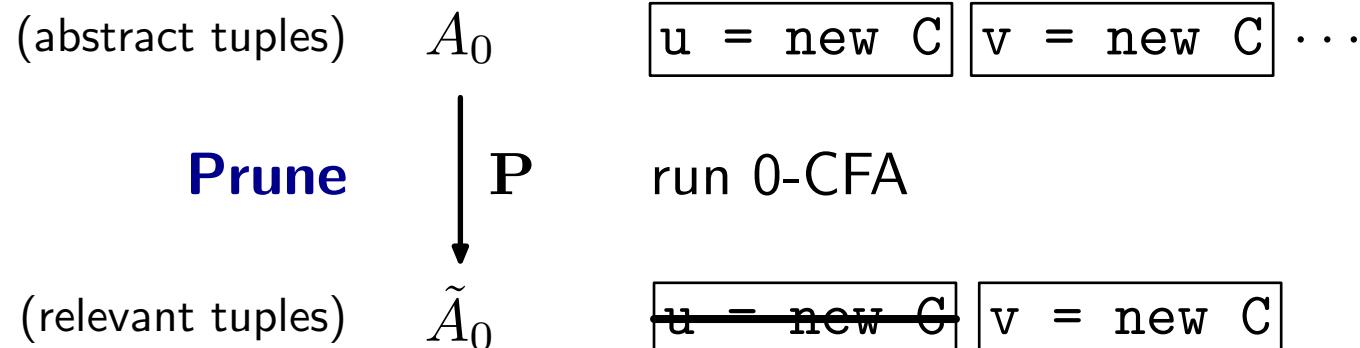
(abstract tuples) A_0

`u = new C` `v = new C` ...

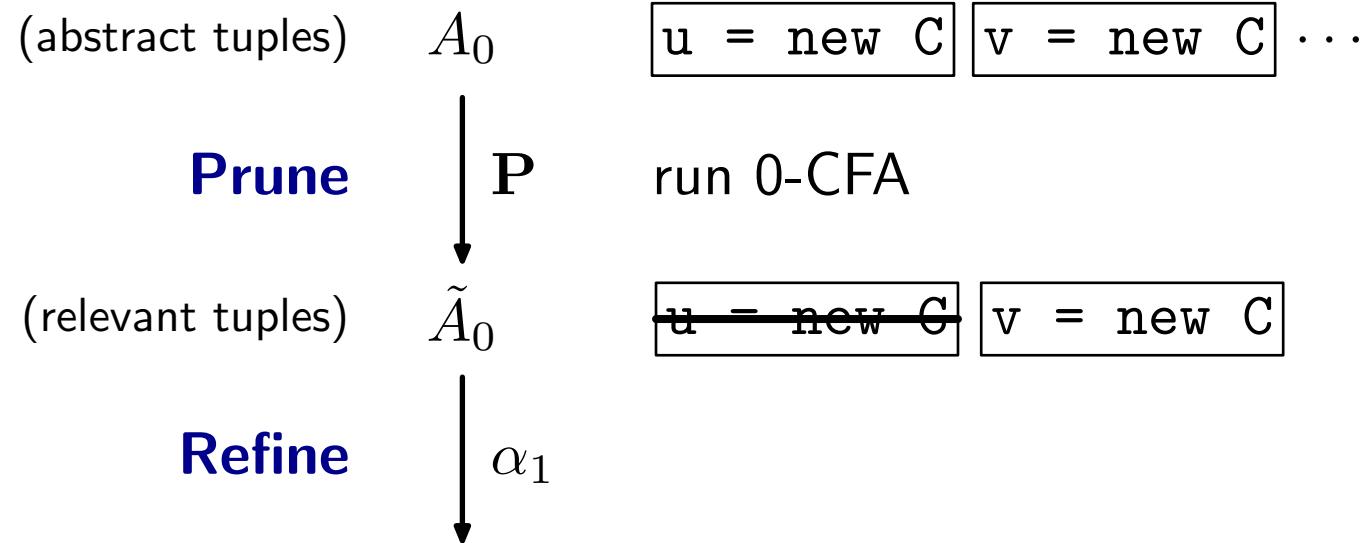
Prune and Refine



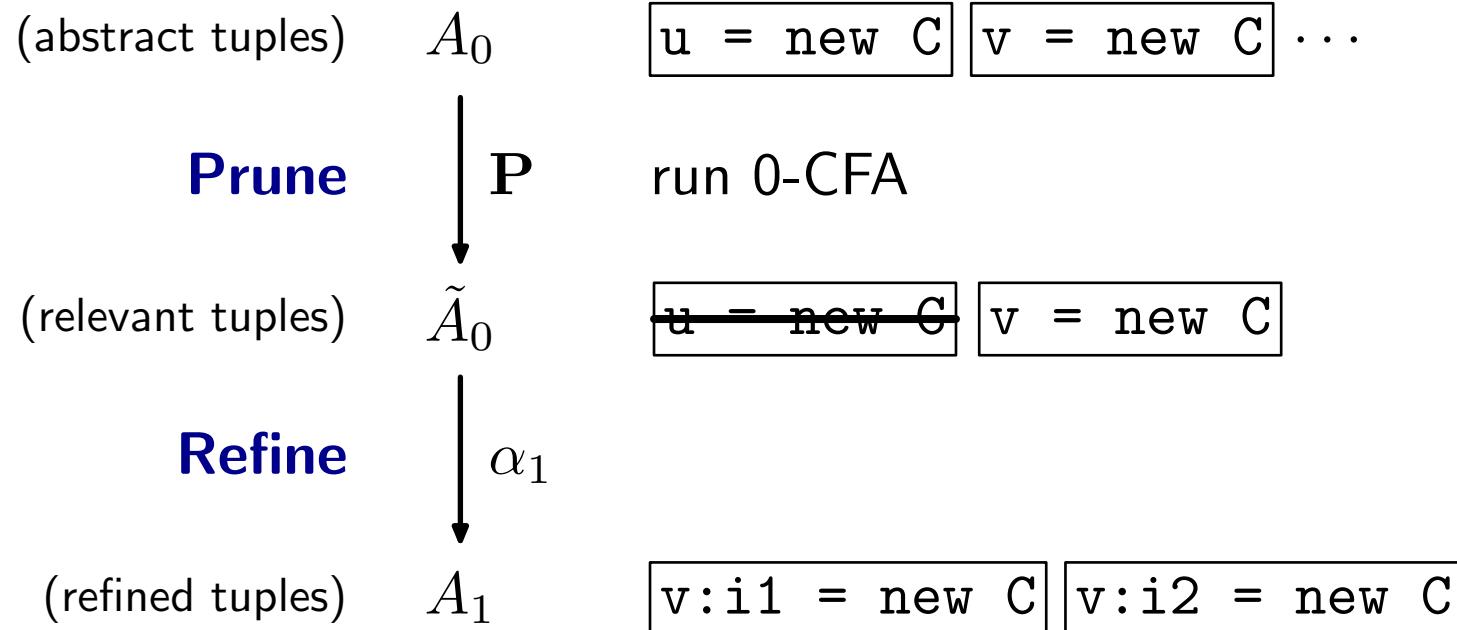
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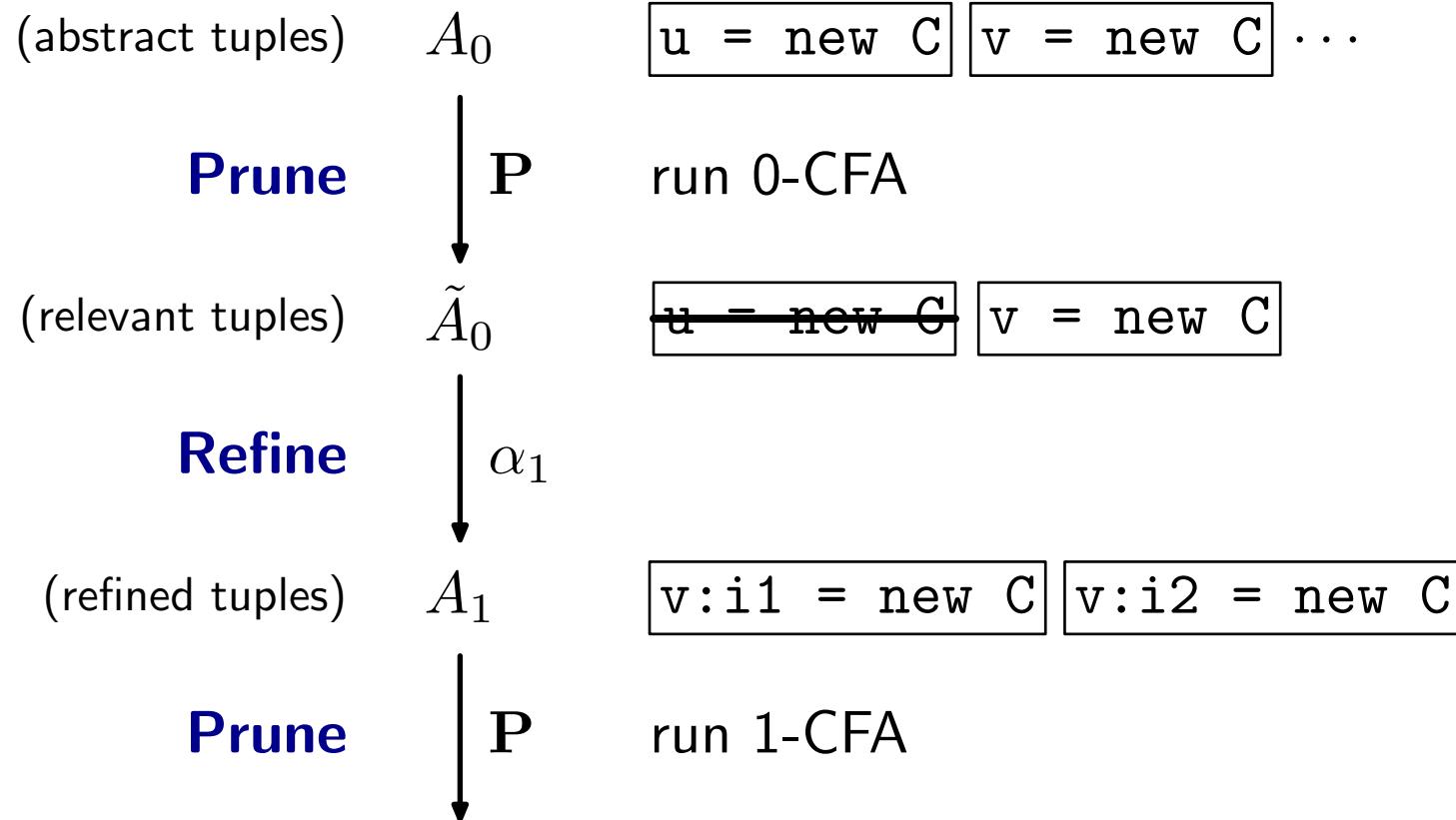
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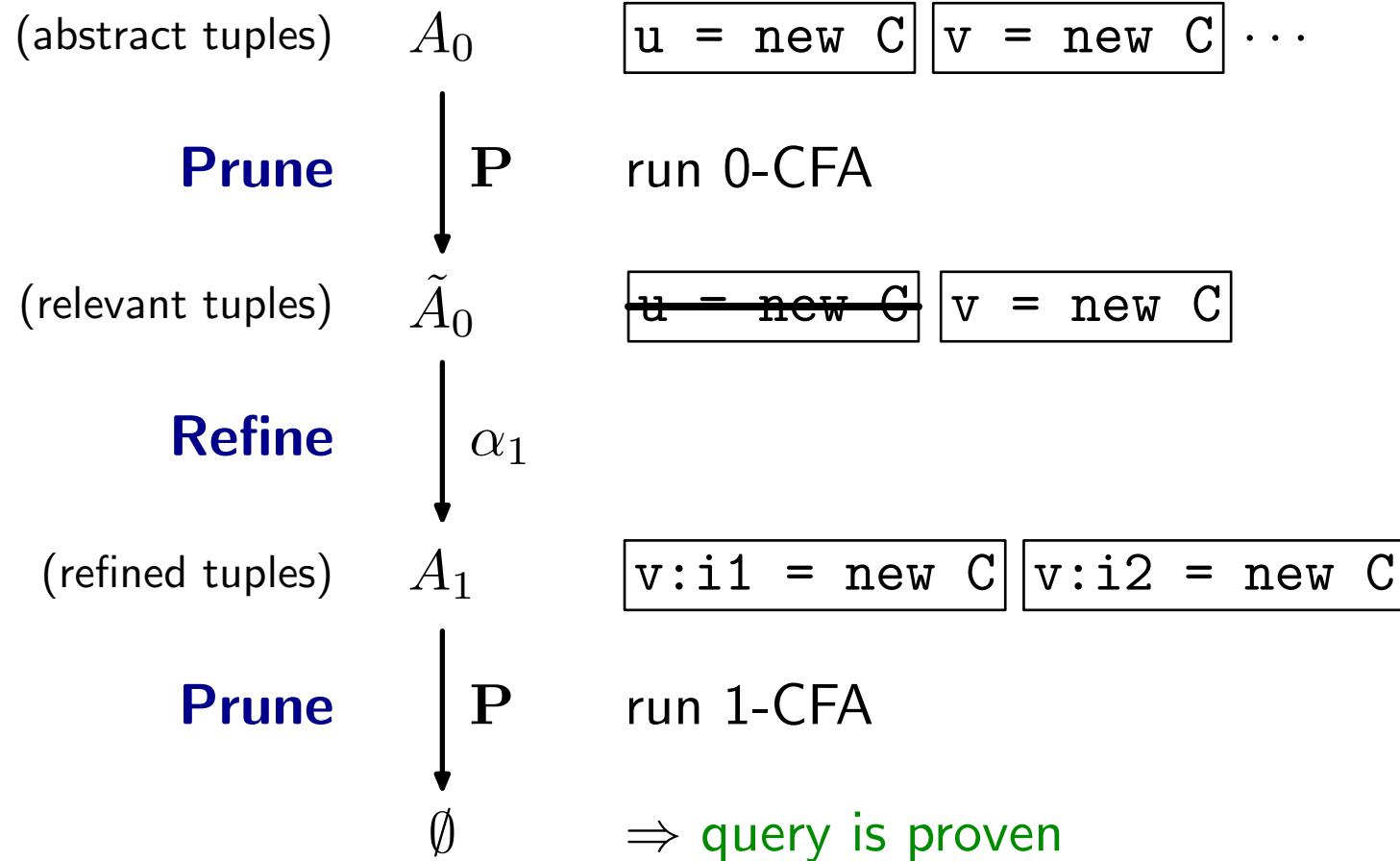
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Prune-Refine Algorithm

Input:

Sequence of abstractions: $\alpha_0 \preceq \alpha_1 \preceq \alpha_2 \preceq \dots$

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A_0 , initial set of tuples

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For $t = 0, 1, 2, \dots$:

Prune: $\tilde{A}_t = \mathbf{P}(A_t)$. If $\tilde{A}_t = \emptyset$: return proven.

Refine: $A_{t+1} = \alpha_{t+1}(\tilde{A}_t)$.

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Main Result:

Prune-Refine after t iterations

fast

=

Full Analysis on α_t

slow

Rest of Talk

Pre-Pruning Extension

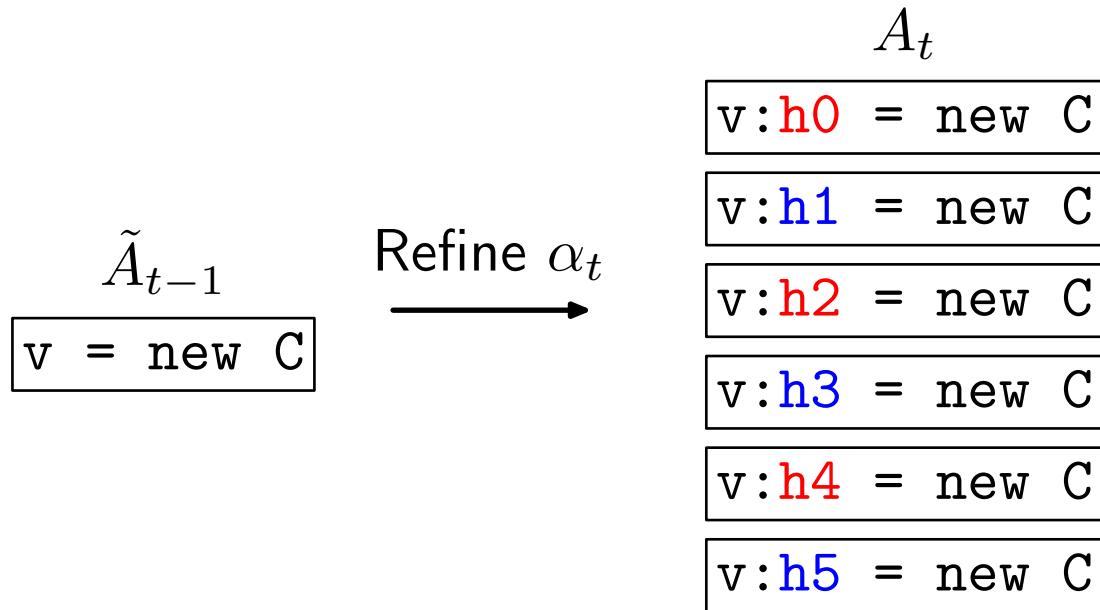
Experiments

Pre-Pruning

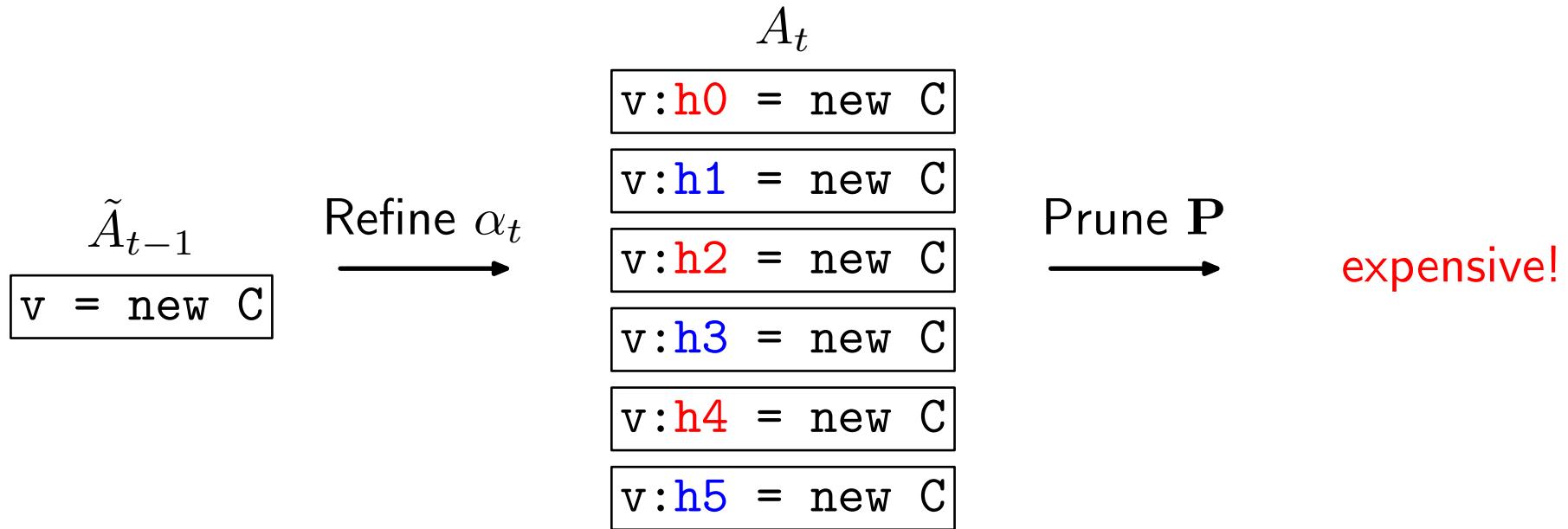
\tilde{A}_{t-1}

v = new C

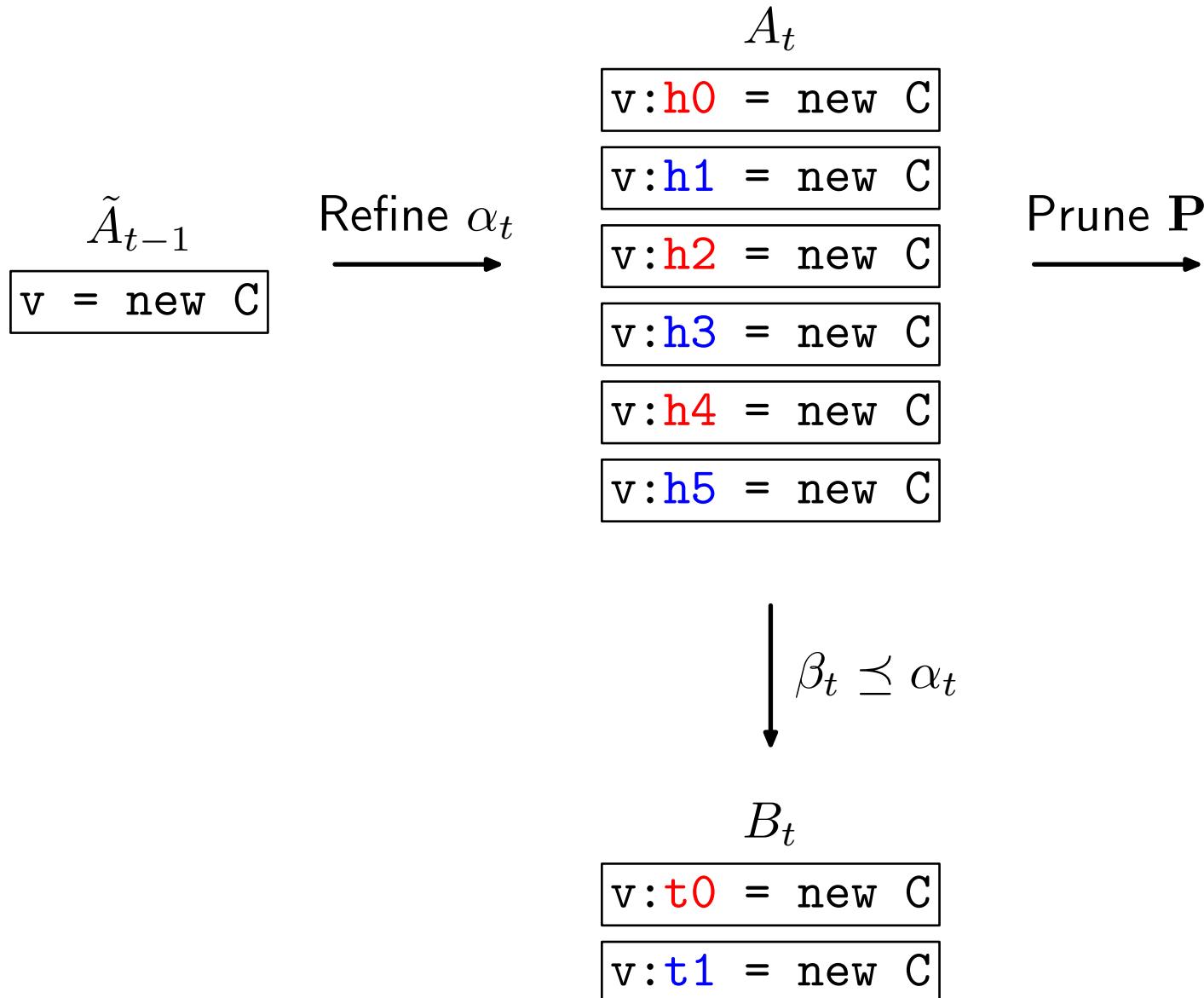
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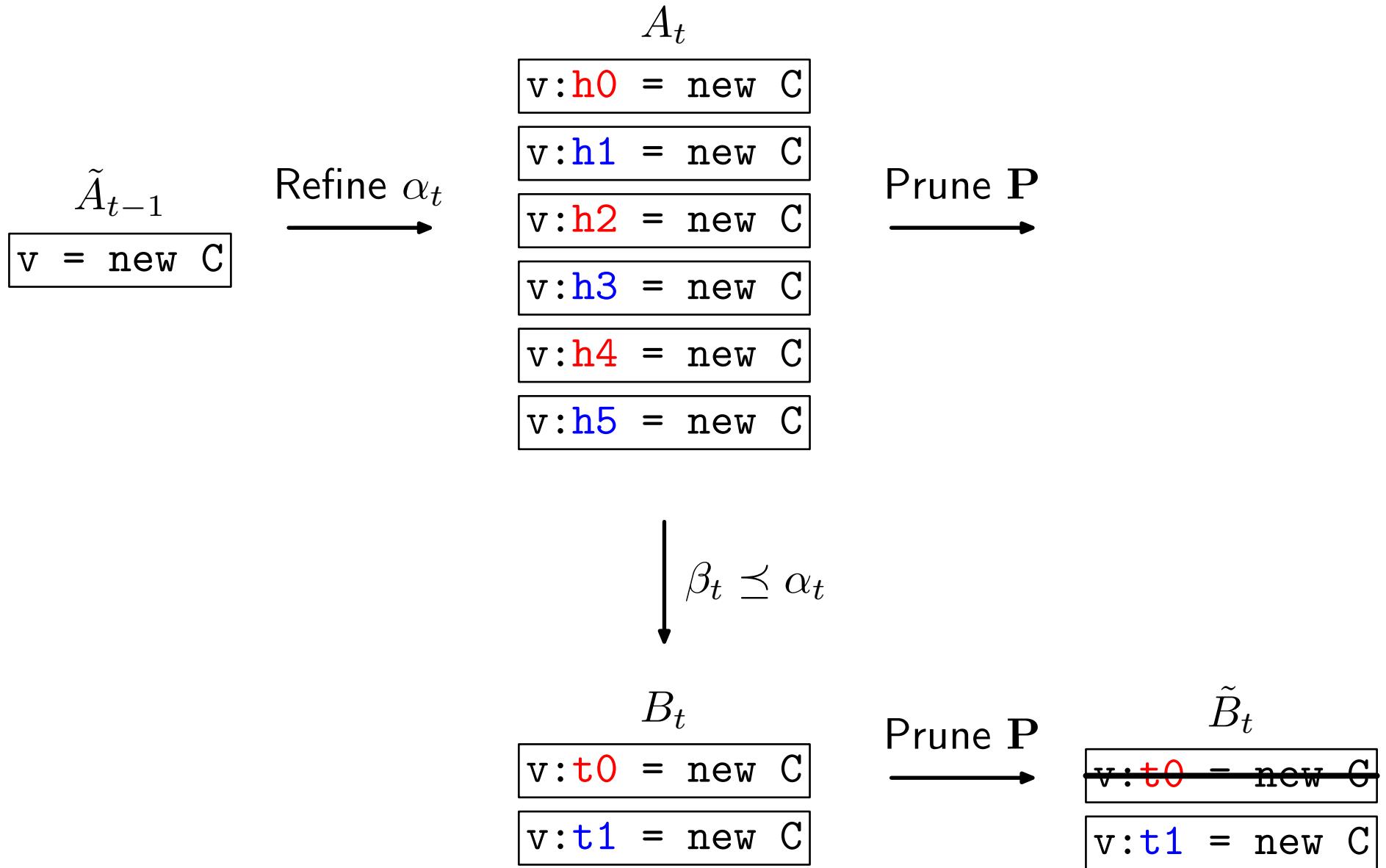
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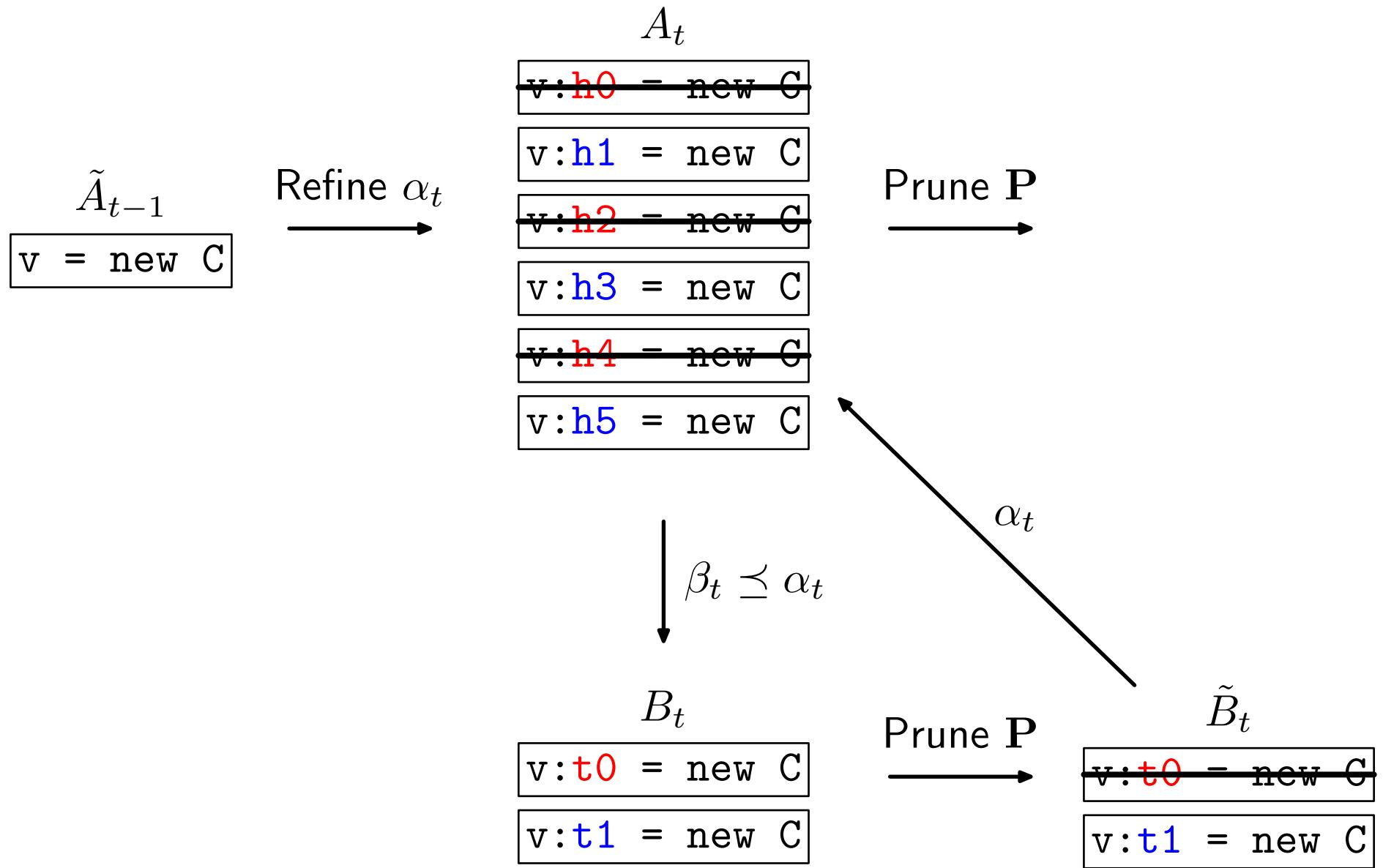
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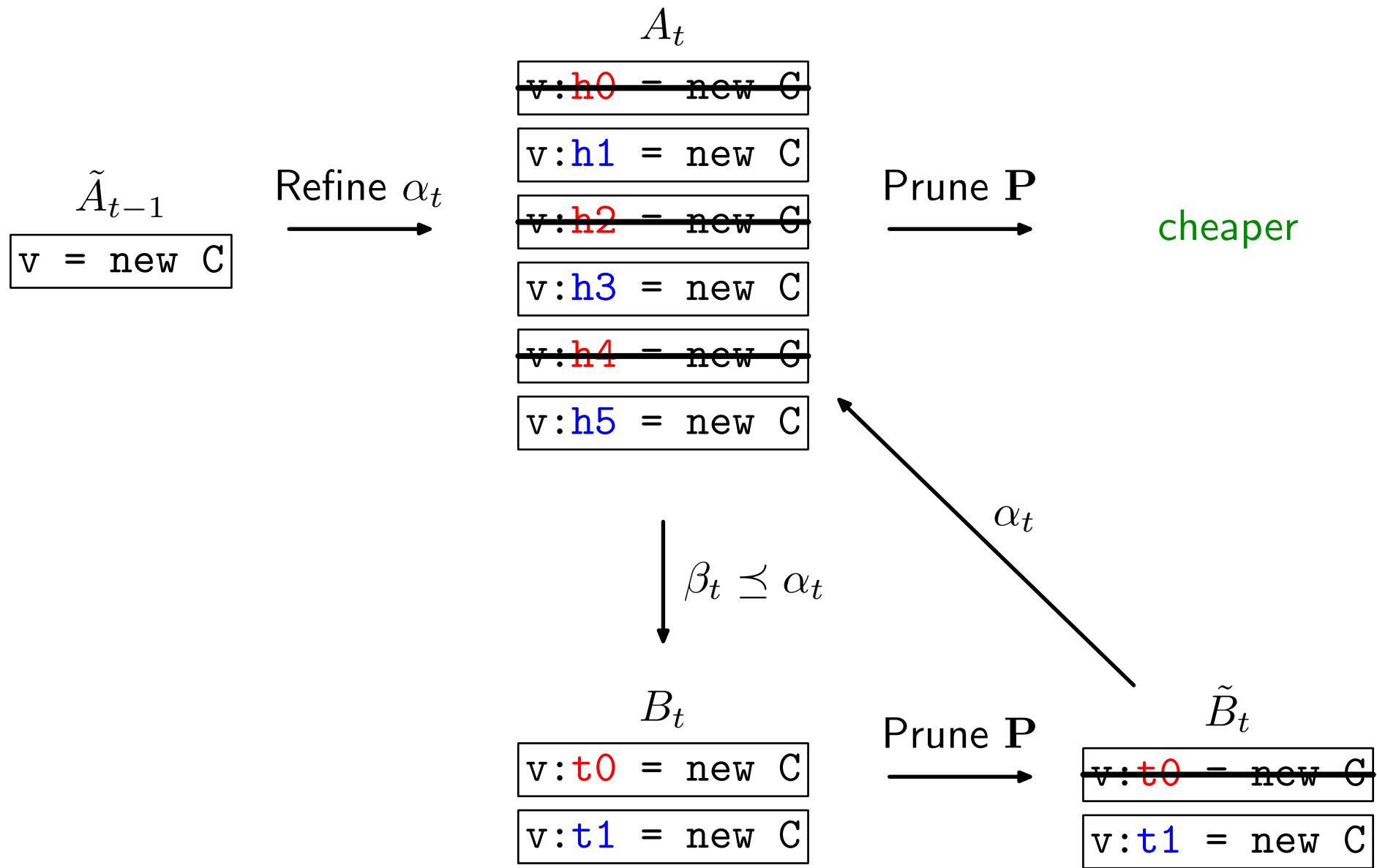
Pre-Pruning



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Which Abstractions for Pre-Pruning?

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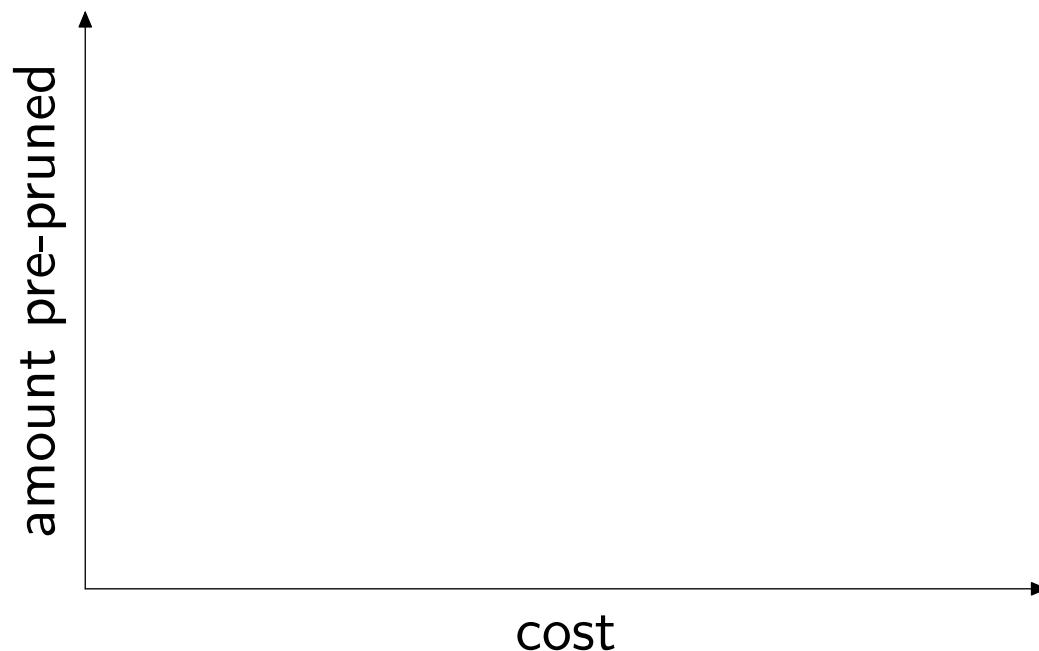
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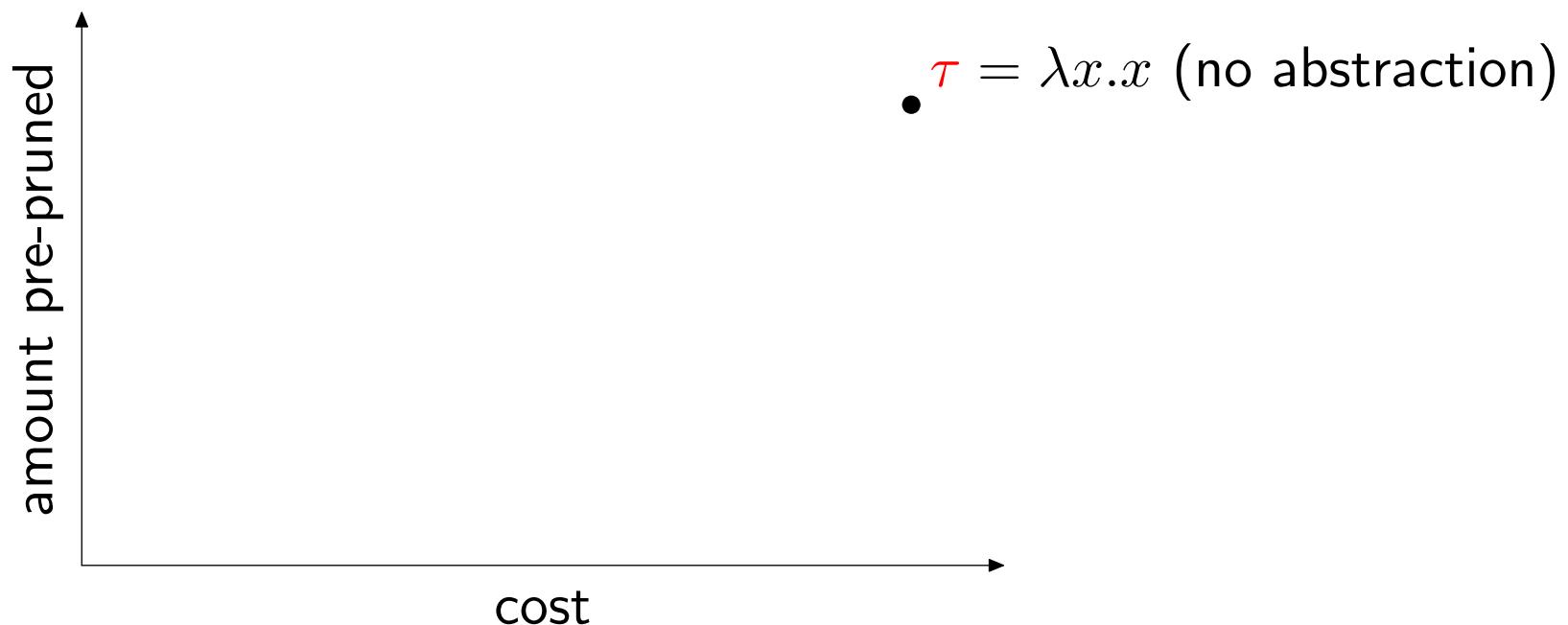
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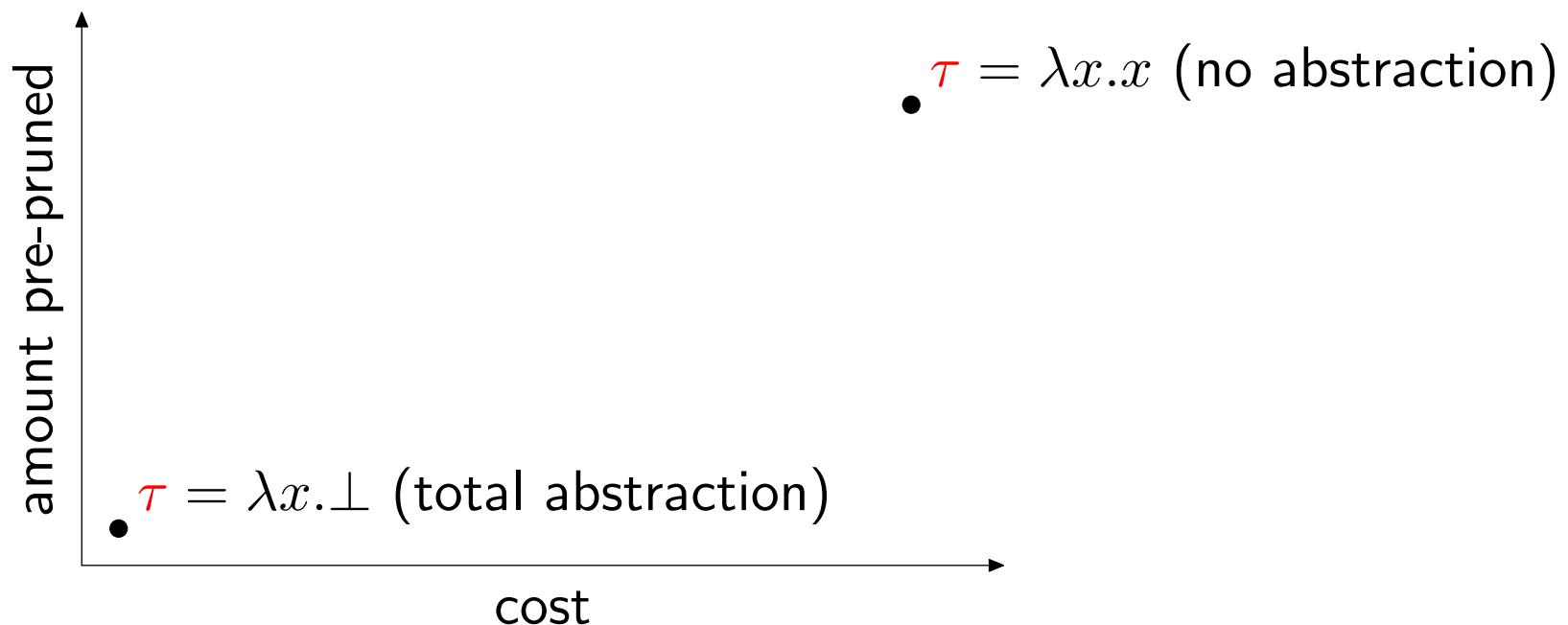
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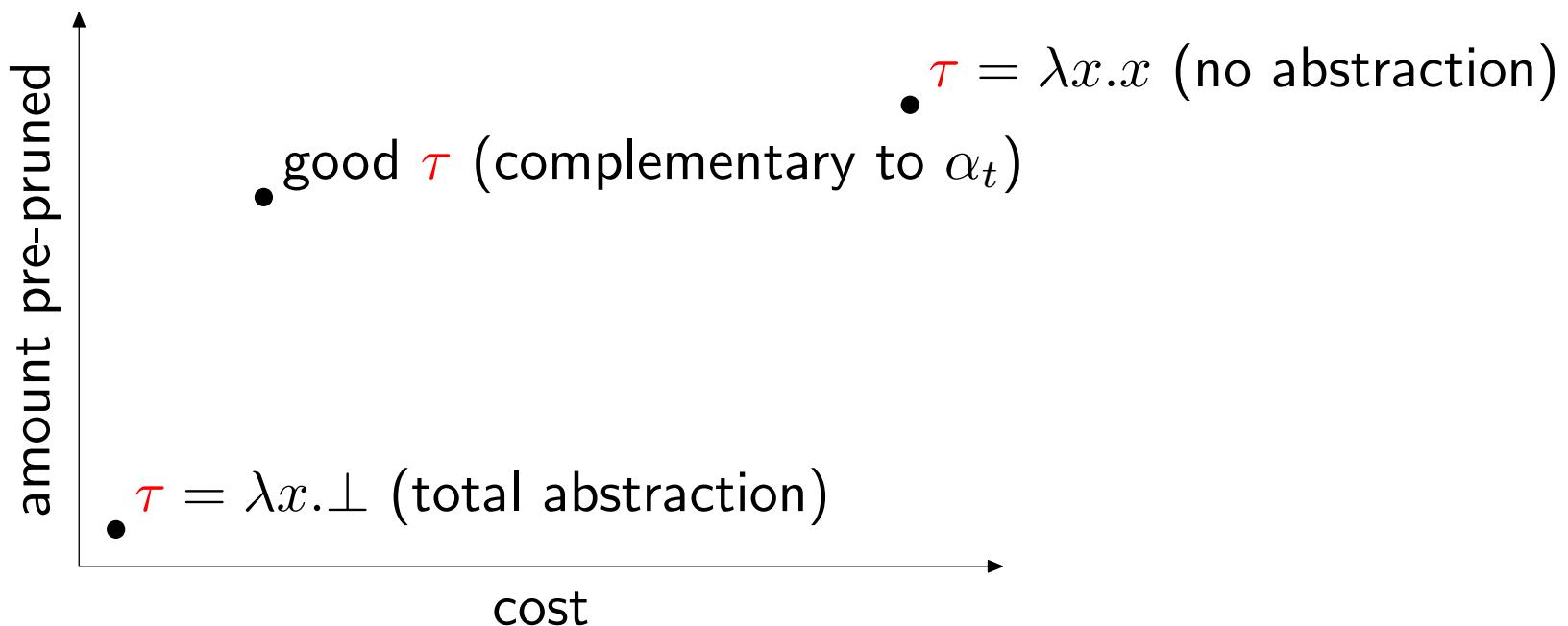
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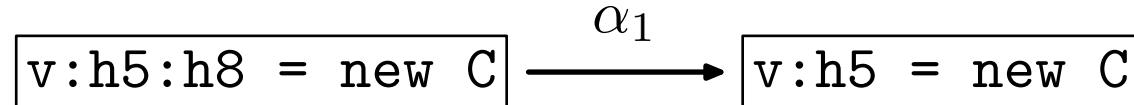
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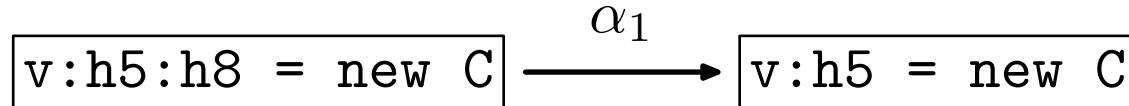
Type-Based Abstractions for Pre-Pruning

k -limited: $\alpha_k = \text{take length } k \text{ prefix}$

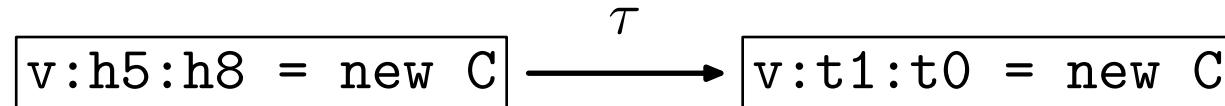


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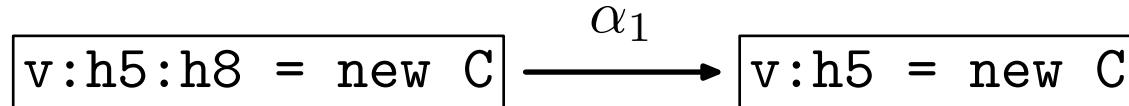


Type-based: $\tau = \text{replace alloc. sites with types}$ [Smaragdakis et al. 2011]

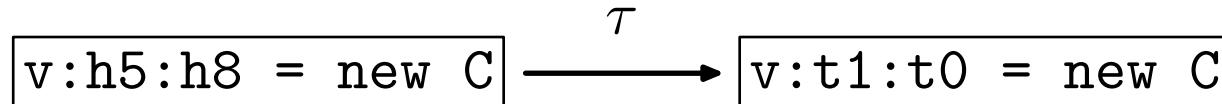


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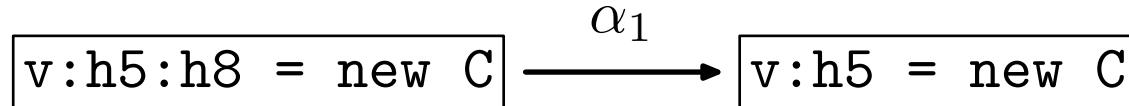
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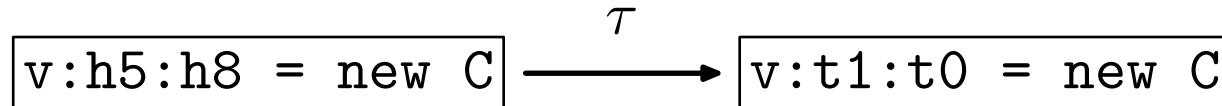
We use $\tau = \text{type of containing class} \times \text{type of allocation site}$

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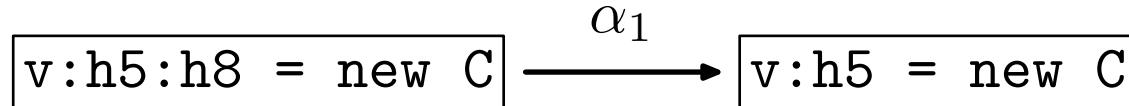


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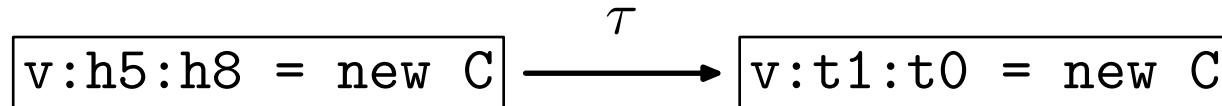
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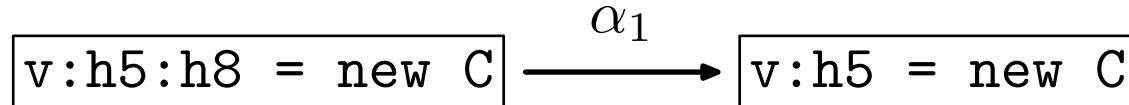
We use τ = type of containing class \times type of allocation site

```
class C1 {  
    h1:    x = new C2  
}
```

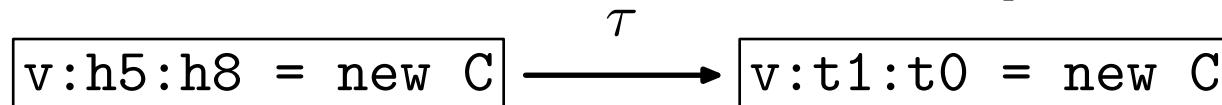
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Type-Based Abstractions for Pre-Pruning

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Composed: $\beta_1 = \alpha_1 \circ \tau$



Rest of Talk

Pre-Pruning Extension

Experiments

Experimental Setup

Clients (based on flow-insensitive k -object-sensitivity):

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Benchmarks:

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hedc	web crawler	151K	1,494
weblech	website downloading and mirroring tool	230K	2,545
lusearch	text indexing and search tool	267K	2,822
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Details:

64-bit IBM J9VM 1.6, Chord with bddbddb Datalog solver

Terminate a process if it exceeds 8GB of memory

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Methods:

- | no pruning

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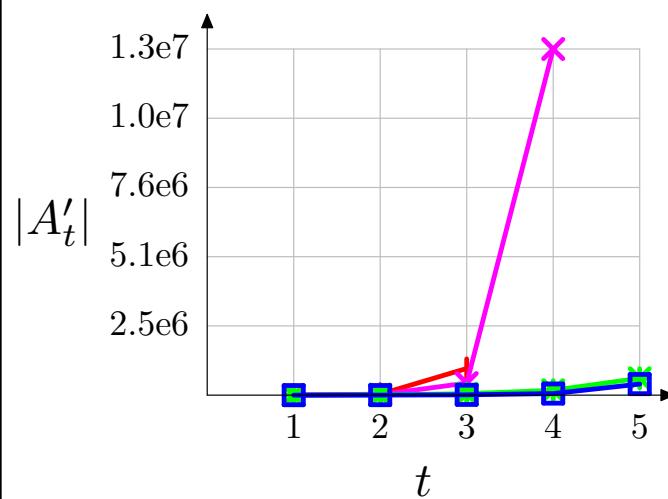
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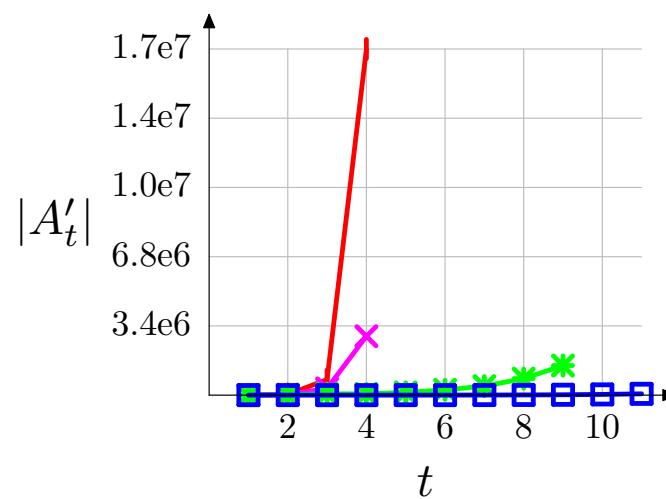
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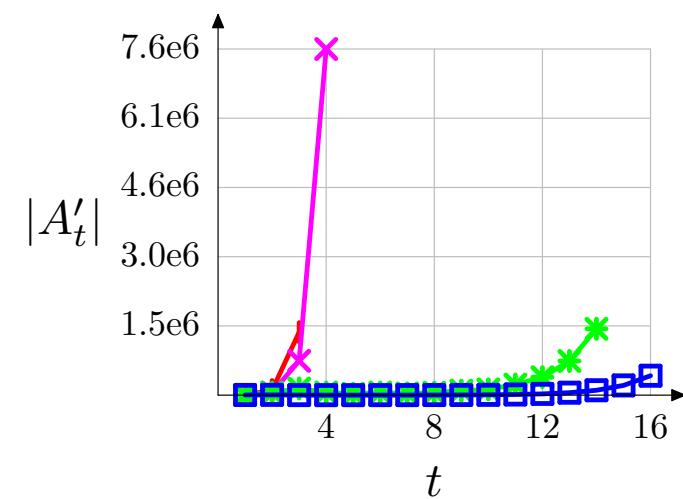
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(b) DOWNCAST/lusearch



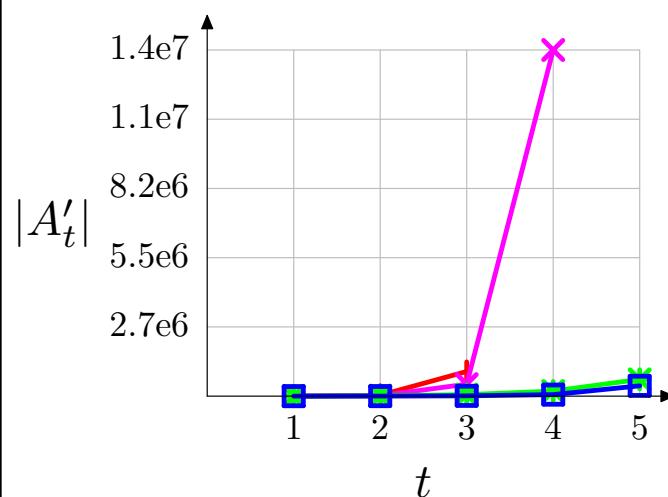
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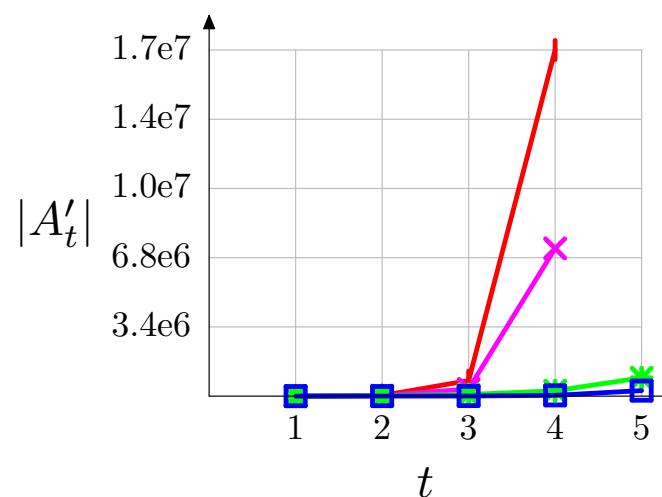
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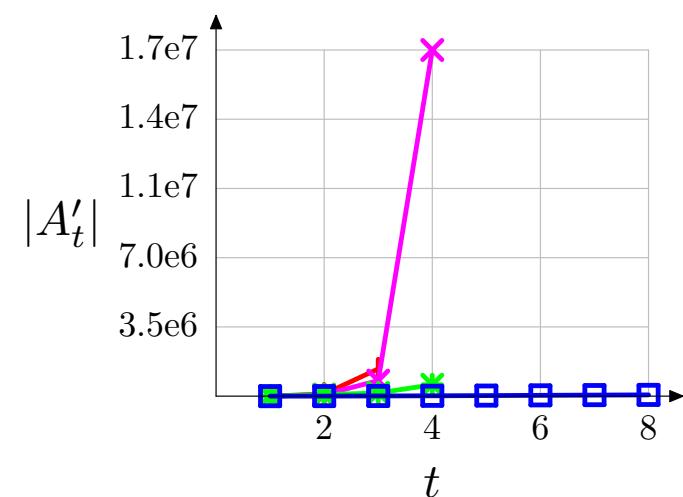
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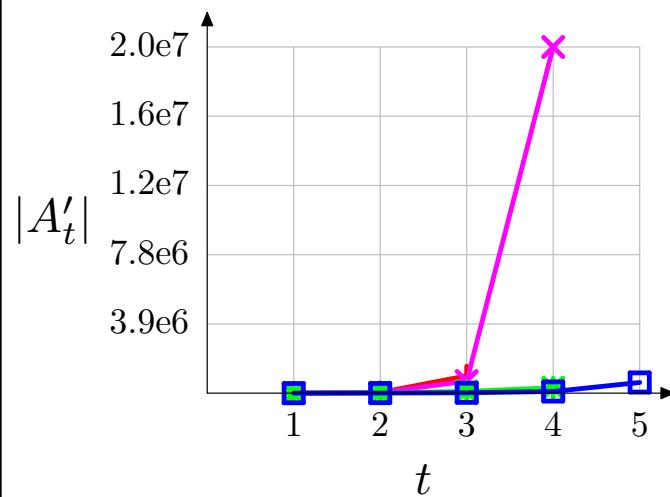
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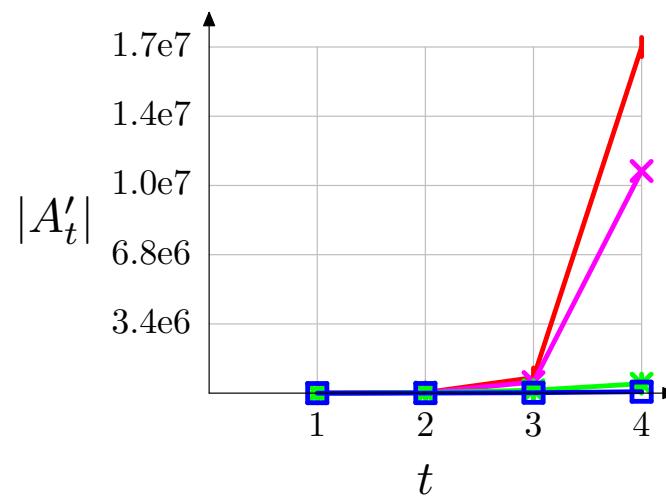
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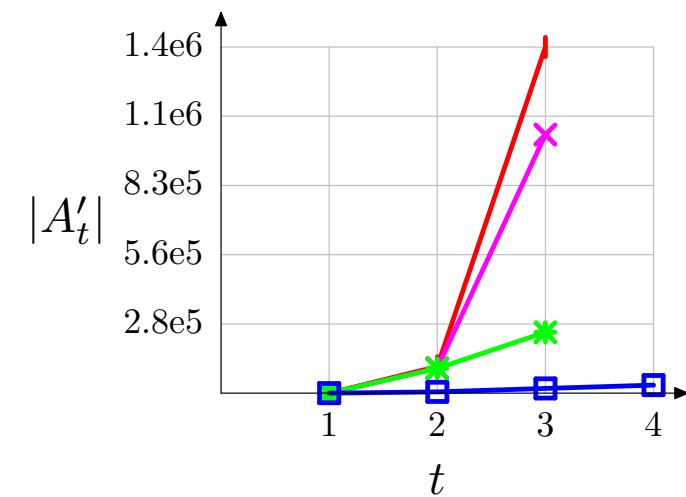
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In each iteration, what fraction of tuples are kept?

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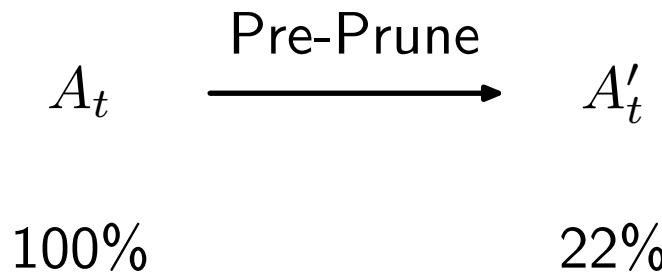
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A_t

100%

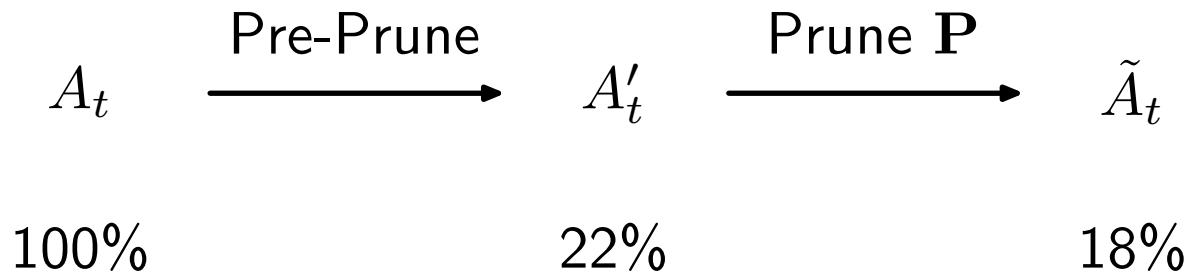
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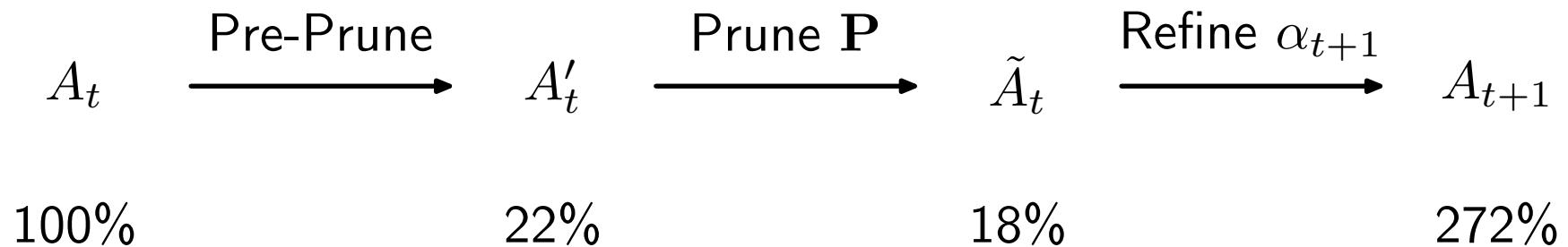
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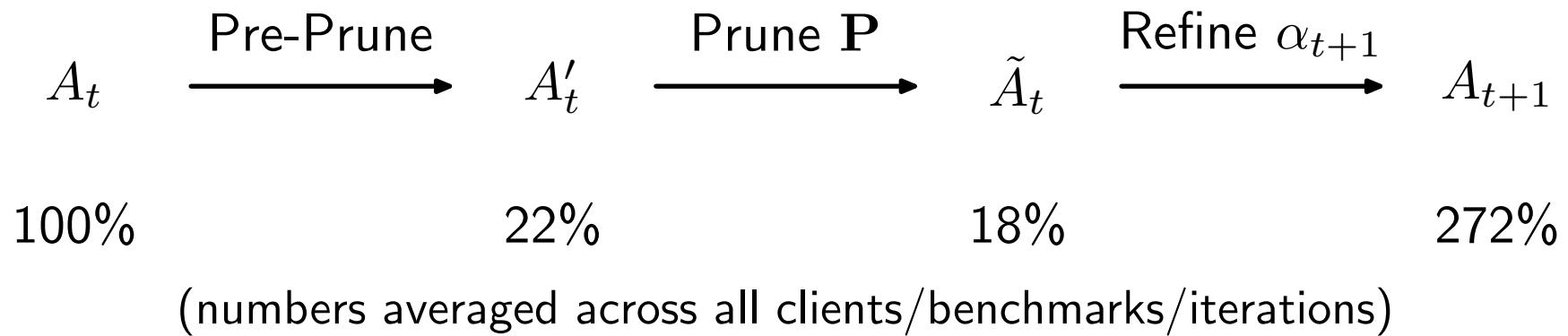
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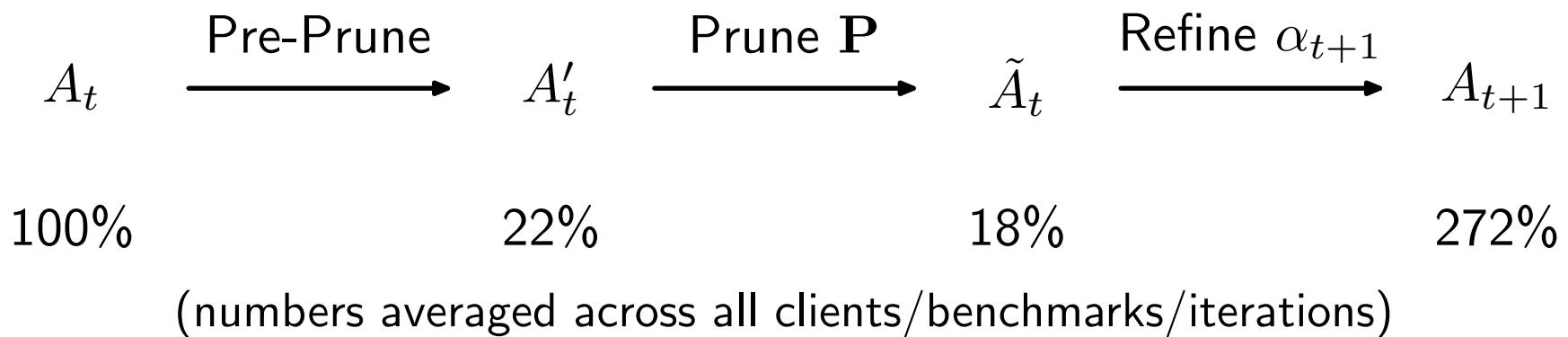
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Take Away: Pruning (especially pre-pruning) helps a lot to maintain tractability

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DOWNCAST/ weblech	24	14	6	6	-
DOWNCAST/ lusearch	36	14	6	5	5
DOWNCAST/ avrora	12	10	6	6	6
MONOSITE/ elevator	1	1	1	1	1
MONOSITE/ hedc	164	149	149	149	-
MONOSITE/ weblech	273	258	252	252	-
MONOSITE/ lusearch	593	454	447	447	-
MONOSITE/ avrora	288	278	272	-	-
RACE/ elevator	475	440	437	437	437
RACE/ hedc	23,033	22,043	21,966	-	-
RACE/ weblech	7,286	4,742	4,669	-	-
RACE/ lusearch	33,845	23,509	16,957	-	-
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Take Away: By using Prune-Refine, able to prove two additional queries

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<http://code.google.com/p/jchord>

Thank you!