Compacting Points-To Sets through Object Clustering

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OOPSLA '21

Points-To Analysis

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3. Build def-use graph.
4. Perform flow-sensitive analysis on def-use graph, not control-flow graph.

Motivation

Why do compact points-to set representations matter?

Program	Program Points	Top-Level Variables	Memory Objects	Average PTS	Largest PTS	SFS Unions
dhcpcd	57 168	63 196	3701	223.55	265	90 785 902
gawk	279 931	141 136	4784	434.81	811	2 275 388 148
bash	254 314	149 070	4339	244.57	324	531 039 266
mutt	360 535	178 147	7169	379.47	1238	1 347 064 278
lynx	579 285	237 252	7917	198.02	1129	4 829 162 478
xpdf	440 418	388 859	19 101	87.78	1590	12 423 325 697
ruby	795 643	670 649	20 235	2.68	1726	13 502 095 022
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$$\{\ 0,\ 3,\qquad\qquad 8,9,\quad \}$$
$$[\,\langle 1001\rangle, \langle 0000\rangle, \langle 1100\rangle\,]$$

($\langle \times\times\times\times \rangle$ is a 4-bit word.)

Bit-Vectors: Fast Unions

$$
\begin{array}{lcccccc}
 & [& w_1, & w_2, & \dots, & w_n &] \\
| & [& w'_1, & w'_2, & \dots, & w'_n &] \\
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 & [& w_1 | w'_1, & w_2 | w'_2, & \dots, & w_n | w'_n &].
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- Compact; very little metadata.

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One word required.

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Given a points-to set P with n objects, word size of $\mathcal{W}$, the minimum number of words required to represent P as a bit-vector is

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$pt(p) = \{o_1, o_2, o_3, o_4, o_5\}$ requires at minimum $\left\lceil \frac{n}{\mathcal{W}} \right\rceil = \left\lceil \frac{5}{4} \right\rceil = 2$ words to represent.

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Auxiliary analysis soundly over-approximates main analysis...

$$\text{Good mapping for auxiliary analysis} \xrightarrow{\textit{probably}} \text{Good mapping for main analysis.}$$

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2. f is some offset multiplier for where the identifiers, m_{x_i}, start.

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Whilst also ensuring the mapping is 1-to-1; for each i, j, $i \neq j$:

$$\left| m_i - m_j \right| > 0 \tag{C2}$$

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Definition

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With $\mathcal{W} = 4$, $w = 1$ for all 3 sets, but:

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- There are 5 objects in total.

Pigeonhole Principle

Definition

Pigeonhole principle. Given n items to be spread amongst m containers, $n > m$, at least one container must contain more than one item.

Consider $P_1 = \{o_1, o_2\}$, $P_2 = \{o_1, o_3, o_4\}$, $P_3 = \{o_2, o_5\}$

- o_1 should be close to o_2, o_3, and o_4
- o_2 should be close to o_1 and o_5.

With $\mathcal{W} = 4$, $w = 1$ for all 3 sets, but:

- The sets overlap.
- There are 5 objects in total.

Pigeonhole principle prevents a perfect solution

Integer Programming Formulation

For each points-to set P:

$$\begin{aligned} m_{x_i} &\geq f_P \cdot \mathcal{W} \\ m_{x_i} &< f_P \cdot \mathcal{W} + w_P \cdot \mathcal{W} \\ f_P &\geq 0 \end{aligned} \tag{C1}$$

Whilst also ensuring the mapping is 1-to-1; for each i, j, $i \neq j$:

$$\left| m_i - m_j \right| > 0 \tag{C2}$$

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$$\begin{aligned} m_{x_i} &\geq f_P \cdot \mathcal{W} \\ m_{x_i} &< f_P \cdot \mathcal{W} + w_P \cdot \mathcal{W} + \boxed{t_P \cdot \mathcal{W}} \\ f_P &\geq 0 \end{aligned} \tag{C1}$$

Whilst also ensuring the mapping is 1-to-1; for each i, j, $i \neq j$:

$$\left| m_i - m_j \right| > 0 \tag{C2}$$

Optimise for minimum tolerances: $t_{P_1} + \cdots + t_{P_n}$.

Integer Programming Formulation

Consider $P_1 = \{o_1, o_2\}$, $P_2 = \{o_1, o_3, o_4\}$, $P_3 = \{o_2, o_5\}$, $\mathcal{W} = 4$

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$m_1 \geq 4 \cdot f_{P_1}$

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$$m_1 < 4 \cdot f_{P_1} + 4 \cdot \left\lceil \frac{2}{4} \right\rceil + 4 \cdot t_{P_1}$$

Integer Programming Formulation

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Integer Programming Formulation

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\end{aligned}
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& m_5 \geq 4 \cdot f_{P_2} \\
& m_5 < 4 \cdot f_{P_2} + 4 \cdot \left\lceil \tfrac{2}{4} \right\rceil + 4 \cdot t_{P_2} \\
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m_5 &< 4 \cdot f_{P_2} + 4 \cdot \left\lceil \tfrac{2}{4} \right\rceil + 4 \cdot t_{P_2} \\
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$$

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m_2 &< 4 \cdot f_{P_3} + 4 \cdot \left\lceil \tfrac{2}{4} \right\rceil + 4 \cdot t_{P_3} \\
m_5 &\geq 4 \cdot f_{P_3} \\
m_5 &< 4 \cdot f_{P_3} + 4 \cdot \left\lceil \tfrac{2}{4} \right\rceil + 4 \cdot t_{P_3} \\
f_{P_3} &\geq 0
\end{aligned}
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Consider $P_1 = \{o_1, o_2\}$, $P_2 = \{o_1, o_3, o_4\}$, $P_3 = \{o_2, o_5\}$, $\mathcal{W} = 4$

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& m_1 \geq 4 \cdot f_{P_1} \\
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& m_5 \geq 4 \cdot f_{P_2} \\
& m_5 < 4 \cdot f_{P_2} + 4 \cdot \left\lceil \tfrac{2}{4} \right\rceil + 4 \cdot t_{P_2} \\
& f_{P_2} \geq 0
\end{aligned}
$$

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\begin{aligned}
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& m_2 < 4 \cdot f_{P_3} + 4 \cdot \left\lceil \tfrac{2}{4} \right\rceil + 4 \cdot t_{P_3} \\
& m_5 \geq 4 \cdot f_{P_3} \\
& m_5 < 4 \cdot f_{P_3} + 4 \cdot \left\lceil \tfrac{2}{4} \right\rceil + 4 \cdot t_{P_3} \\
& f_{P_3} \geq 0
\end{aligned}
$$

$$
\begin{gathered}
|m_1 - m_2| > 0,\ |m_1 - m_3| > 0,\ |m_1 - m_4| > 0,\ |m_1 - m_5| > 0,\ |m_2 - m_3| > 0, \\
|m_2 - m_4| > 0,\ |m_2 - m_5| > 0,\ |m_3 - m_4| > 0,\ |m_3 - m_5| > 0,\ |m_4 - m_5| > 0
\end{gathered}
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Integer Programming Formulation

Consider $P_1 = \{o_1, o_2\}$, $P_2 = \{o_1, o_3, o_4\}$, $P_3 = \{o_2, o_5\}$, $\mathcal{W} = 4$

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\begin{aligned}
&m_1 \geq 4 \cdot f_{P_1} \\
&m_1 < 4 \cdot f_{P_1} + 4 \cdot \left\lceil \tfrac{2}{4} \right\rceil + 4 \cdot t_{P_1} \\
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&f_{P_2} \geq 0
\end{aligned}
$$

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&m_2 \geq 4 \cdot f_{P_3} \\
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&m_5 \geq 4 \cdot f_{P_3} \\
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&f_{P_3} \geq 0
\end{aligned}
$$

$$
\begin{gathered}
|m_1 - m_2| > 0,\ |m_1 - m_3| > 0,\ |m_1 - m_4| > 0,\ |m_1 - m_5| > 0,\ |m_2 - m_3| > 0, \\
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\end{gathered}
$$

Optimise for minimum $t_{P_1} + t_{P_2} + t_{P_3}$.

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Consider $P_1 = \{o_1, o_2\}$, $P_2 = \{o_1, o_3, o_4\}$, $P_3 = \{o_2, o_5\}$, $\mathcal{W} = 4$

$$\begin{aligned}
&m_1 \geq 4 \cdot f_{P_1} \\
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$$|m_1 - m_2| > 0,\ |m_1 - m_3| > 0,\ |m_1 - m_4| > 0,\ |m_1 - m_5| > 0,\ |m_2 - m_3| > 0,$$
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Optimise for minimum $t_{P_1} + t_{P_2} + t_{P_3}$.

Optimal... but costly! Let's try something more approximate...

Hierarchical Clustering

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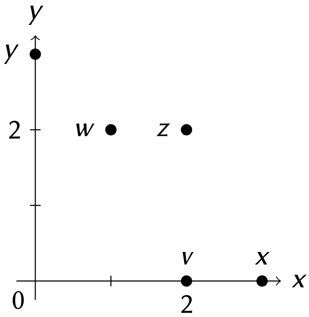

Distance function: Euclidean distance $-\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$.

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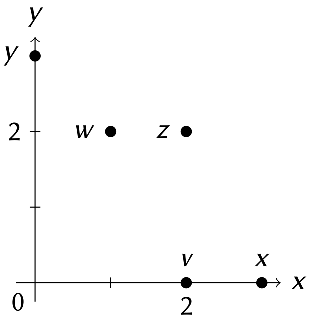

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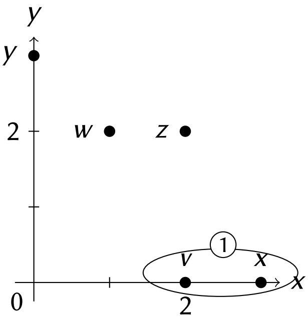

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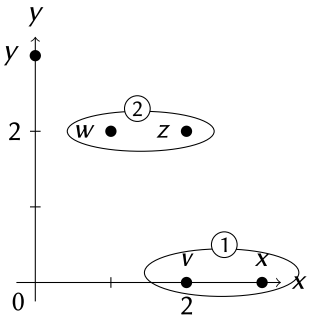

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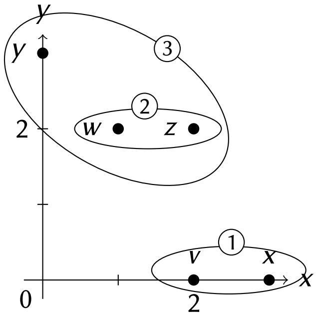

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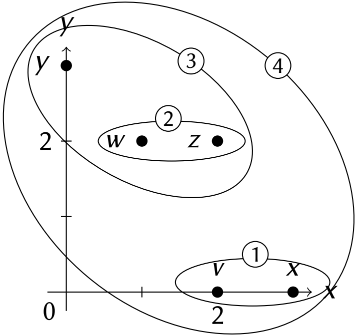

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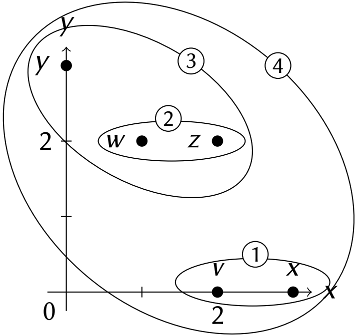

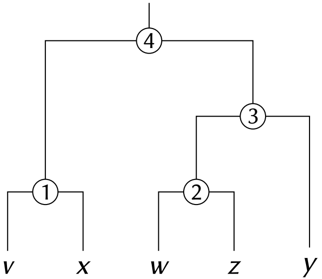

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   - Produces dendrogram.
3. Initialise a counter c to 0.
4. Perform depth-first search on dendrogram.
   - At each leaf containing object o.
     1. Map o to c.
     2. Increment c.

Optimisation: Region-Based Clustering

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Regions with fewer than $\mathcal{W}$ objects can have their objects mapped arbitrarily.

Optimisation: Word-Aligned Identifier Mapping

The first identifier in a region should always start at a word-aligned boundary.

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Example

Consider two regions R_1 and R_2

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Any points-to set in R_2 (subsets of $\{o_d, o_e, o_f\}$) will take one of three forms

$$\begin{aligned} \{\, 0\, [\, \langle 0001 \rangle \,] \,\} &\quad \{o_d\} \\ \{\, 4\, [\, \langle \times \times 00 \rangle \,] \,\} &\quad \{o_e\}, \{o_f\}, \{o_e, o_f\} \\ \{\, 0\, [\, \langle 0001 \rangle, \langle \times \times 00 \rangle \,] \,\} &\quad \{o_d, o_e\}, \{o_d, o_f\}, \{o_d, o_e, o_f\} \end{aligned}$$

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$$\{\, 0\, [\, \langle \times \times \times 0 \rangle \,]\, \},$$

Any points-to set in R_2 (subsets of $\{o_d, o_e, o_f\}$) will take one of three forms

$$\{\, 0\, [\, \langle 0001 \rangle \,]\, \} \quad \{o_d\}$$
$$\{\, 4\, [\, \langle \times \times 00 \rangle \,]\, \} \quad \{o_e\}, \{o_f\}, \{o_e, o_f\}$$
$$\{\, 0\, [\, \langle 0001 \rangle, \langle \times \times 00 \rangle \,]\, \} \quad \{o_d, o_e\}, \{o_d, o_f\}, \{o_d, o_e, o_f\}$$

Optimisation: Word-Aligned Identifier Mapping

The first identifier in a region should always start at a word-aligned boundary.

Example

Instead, consider the mapping

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\begin{aligned}
R_1 &: o_a \mapsto 0 \quad o_b \mapsto 1 \quad o_c \mapsto 2 \\
R_2 &: o_d \mapsto 4 \quad o_e \mapsto 5 \quad o_f \mapsto 6
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As before, any points-to set with objects in R_1 will take the form

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But now, any points-to set with objects in R_2 will take the form

$$\{\, 4\, [\, \langle \times \times \times 0 \rangle \,]\, \}$$

Implementation

- Implemented in LLVM-based points-to analysis framework SVF.
  - SFS algorithm unchanged.
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Evaluation: Word Reduction

Benchmark	**Theoretical**	**Original**	**Single**	**Complete**	**Average**	**Reduction**
dhcpcd	3 317 195	23 911 465	**4 961 417**	6 605 816	5 784 023	4.82 ×
gawk	58 007 460	429 739 789	**82 783 110**	140 588 641	148 836 214	5.19 ×
bash	26 586 881	295 168 808	**31 731 607**	36 861 568	47 120 912	9.30 ×
mutt	51 298 142	548 971 273	**87 213 543**	260 457 927	259 746 461	6.29 ×
lynx	133 664 618	1 015 676 964	**237 113 529**	289 849 510	302 122 259	4.28 ×
xpdf	731 879 787	4 197 513 654	1 558 434 196	1 558 496 134	**1 526 729 185**	2.75 ×
ruby	320 059 196	6 600 730 356	**1 405 659 097**	2 514 836 137	2 186 425 117	4.70 ×
keepassxc	13 770 856	1 399 786 369	**107 456 539**	134 257 502	120 881 288	13.03×
Geo. Mean						5.66×

(**Theoretical** is $\lceil \frac{n}{\mathcal{W}} \rceil$.)

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Speedup: 1.32×

Memory reduction: ≥2.35×

Thank you

Implementation available at https://github.com/SVF-tools/SVF/wiki/Object-Clustering