

## Last Time

- ◆ Major result from this class: Abstract fixpoint approximates concrete fixpoint
- ◆ And requirements this imposes on...
  - > Domain structure
  - > Galois connection between domains
  - > Transfer functions between elements of the abstract domain
- ◆ Partitioning
- ◆ Example domains
- ◆ Widening

- ◆ Homework 4 due today
- ◆ Homework 5 assigned

## Today

- ◆ Combining abstract domains

## Widening

- ◆ Problem: Abstract domains with large or infinite height result in analysis that is slow or non-terminating
- ◆ I.e. for some domains we can't (efficiently) compute:

$$fix = \bigsqcup F^i(\perp, \dots, \perp)$$

- ◆ Solution: Introduce a widening operator  $w$  that composes with the transfer function like this:

$$fixw = \bigsqcup (F \circ w)^i(\perp, \dots, \perp)$$

## Widening

- ◆ As long as  $w$  is monotonic, the analysis remains sound
- ◆ Example widening function for intervals:
  - > For some fixed set of constants, find the smallest interval with bounds chosen from this set that contains starting interval
  - > For example, for the set  $\{-\infty, -10, -1, 1, 10, \infty\}$ 
    - $[0..1]$  goes to  $[-1..1]$
    - $[-5..0]$  goes to  $[-10..1]$
    - $[-15..11]$  goes to  $[-\infty.. \infty]$
  - > Set could be found by looking for constants in the source code

## Widening Example

- ◆ Let's say we want to analyze this code using the interval domain

```
y=0;
while (opaque) {
  x=7;
  x++;
  y++;
}
```

- ◆ Interval analysis does not terminate (quickly)
  - > Result is  $x=[8..8]$ ,  $y=[0..\infty]$

## Widening Example

```

y=0;
while (opaque) {
  x=7;
  x=x+1;
  y=y+1;
}

```

- ◆ Widening with the set of constants  $\{-\infty, 0, 1, 7, \infty\}$ 
  - > Result is  $x=[7..\infty]$ ,  $y=[0..\infty]$

## Widening Discussion

- ◆ Why use widening when we could just define a rapidly-terminating lattice ahead of time?
  - > Widening effectively permits a new sub-lattice to be picked for each program analyzed
  - > Avoids messing with the original, clean domain
  - > Narrowing – can potentially recover some precision by running the original transfer functions after widening has overshot the fixpoint

## Combining Abstract Domains

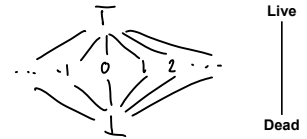
- ◆ Domains can be combined in different ways
- ◆ First we look at why, then how

- ◆ Motivating example program:

```

x = 1;
while (opaque) {
  if (x != 1) {
    x = 2;
  }
}

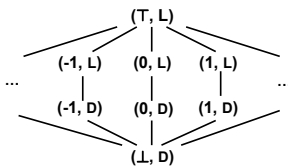
```



- ◆ First analyze using constant propagation
- ◆ Second perform liveness analysis
- ◆ Iterate if needed

## Direct Product of Domains

- ◆ Compute the direct product of the constant and liveness lattices
  - > Lattice is cross product
  - > Transfer functions are created by applying original functions element-wise
- ◆ For programs with one variable:



## Direct Product

- ◆ Now analyze using the combined domain

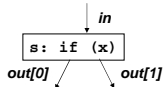
```

x = 1;
while (opaque) {
  if (x != 1) {
    x = 2;
  }
}

```

- ◆ What happens?
- ◆ What's going on here?

## Direct Product



For constants:

$$\begin{aligned} out[0] &= in \wedge \\ out[1] &= in \end{aligned}$$

For liveness:

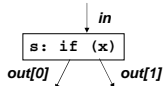
$$\begin{aligned} out[0] &= \perp \text{ if } x \neq 0 \text{ or } in = \perp \\ &\wedge \\ out[1] &= \perp \text{ if } x = 0 \text{ or } in = \perp \end{aligned}$$

Here 0 on the right side is literal zero

## Reduced Product of Domains

- ◆ **Problem: Domains failed to interact**
  - Direct product is not any better than running analyses one after the other
- ◆ **Solution: Make the domains interact**
  - Requires some new transfer functions!
  - The most precise combination of domains is called the reduced product

## Reduced Product



For constants:

$$\begin{aligned} out[0] &= in \wedge \\ out[1] &= in \end{aligned}$$

For liveness:

$$\begin{aligned} out[0] &= \perp \text{ if } x \neq 0 \text{ or } in = \perp \\ &\wedge \\ out[1] &= \perp \text{ if } x = 0 \text{ or } in = \perp \end{aligned}$$

Here 0 on the right side is an element of the constant lattice

## Back to Example

```
x = 1;
while (opaque) {
  if (x != 1) {
    x = 2;
  }
}
```

- ◆ **Finally we get the desired result**
  - This analysis is called “conditional constant propagation”
  - The original paper on CCP is a classic
  - CCP is used in real compilers, such as gcc

## Reduced Product Background

- ◆ Recall the requirement for local transfer function  $F_A$ :
  - $\alpha \circ F_C \circ \gamma \sqsubseteq_A F_A$
- ◆ In other words, the optimal transfer function is obtained by:
  - Concretizing the abstract value(s)
  - Applying the concrete transfer function
  - Abstracting the resulting set of concrete values

## Reduced Product

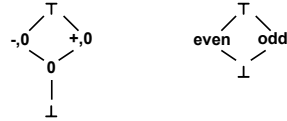
- ◆ A reduced product transfer function is defined as (and may be computed by):
  - Concretizing the abstract values in all domains
  - Applying the concrete transfer functions
  - Intersecting the resulting sets of concrete values
  - Abstracting the intersection
- ◆ Not generally computable
  - Just like good transfer functions in the first place
  - Efficient reduced product implementations require hard work

## Another way to look at it

- ◆ Individual dataflow analyses can be internally optimistic
  - > This means: Abstract states start at the bottom
- ◆ However, dataflow results must be pessimistic
- ◆ Lack of optimism across different analyses results in missed opportunities
- ◆ Reduced product means maximal sharing of optimism across domains

## Another Example

- ◆ Consider lattices of signs, parity, and constants



- ◆ Exercise: Give a nontrivial transfer function from the reduced product domain
  - >  $(+,0, \text{odd}, T) - (T, T, 1) =$
  - >  $(+,0, \text{even}, T)$

## Another Example

```

a = 5;
b = 10;
p = &a;
while (*p > 5) {
  p = &b;
  b = 20;
}

```

- ◆ Does CCP do the trick here?
- ◆ What needs to be added?

## Domain Products

- ◆ Direct product is easy but does not win
- ◆ Reduced product is the most precise but is not computable
- ◆ Products between these exist
  - > One is Granger's product

## Granger's Product

- ◆ Let  $\sigma_1 : D_1 \times D_2 \rightarrow D_1$  such that
  - >  $\sigma_1(d_1, d_2) \leq d_1$
  - >  $\gamma(\langle \sigma_1(d_1, d_2), d_2 \rangle) = \gamma(\langle d_1, d_2 \rangle)$
- ◆ Let  $\sigma_2 : D_1 \times D_2 \rightarrow D_2$  such that
  - >  $\sigma_2(d_1, d_2) \leq d_2$
  - >  $\gamma(\langle d_1, \sigma_2(d_1, d_2) \rangle) = \gamma(\langle d_1, d_2 \rangle)$
- ◆ To use these, apply the element-wise transfer functions to  $(d_1, d_2)$  as in the direct product, then repeatedly reduce these abstract values using  $\sigma_1$  and  $\sigma_2$  until a fixpoint is reached
- ◆ Simple and efficient
  - > But cannot capture some interactions
  - > Reduction functions need to be designed by hand

- ◆ Abstract interpretations can be compared using a lattice
  - > Partial order is "at least as precise as"
- ◆ Bottom of the lattice is the collecting semantics
- ◆ Top is the trivial domain with one element
- ◆ Direct product is LUB of its component domains
  - > That is, the least precise of all the domains that are at least as precise as either component
  - > Reduced product is always at least as precise as direct

## Summary

- ◆ Different domains discover different information about a program
- ◆ Combining domains permits them to “learn” from each other
- ◆ Combining abstract domains provides a powerful and systematic way to design program analyses
  - > I.e., start with many simple domains and compose them into useful composite domains
  - > Con: Domain combination isn't easy
  - > Pro: May still be easier than designing the composite domain from scratch