

# **High-Assurance Scientific Computing: A Unified Approach**

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**October 14, 2021**

# **Intended Learning Outcomes for today**

- **Mathematical Optimisation as a general software technique**
- **Satisfiability Solving**
- **Path Reachability**
- **Overflow Detection**

# Boundary value analysis (recall)

```
void Prog(double x) {  
    if (x <= 1.0) x++;  
    double y = x * x;  
    if (y <= 4.0) x--;  
}
```

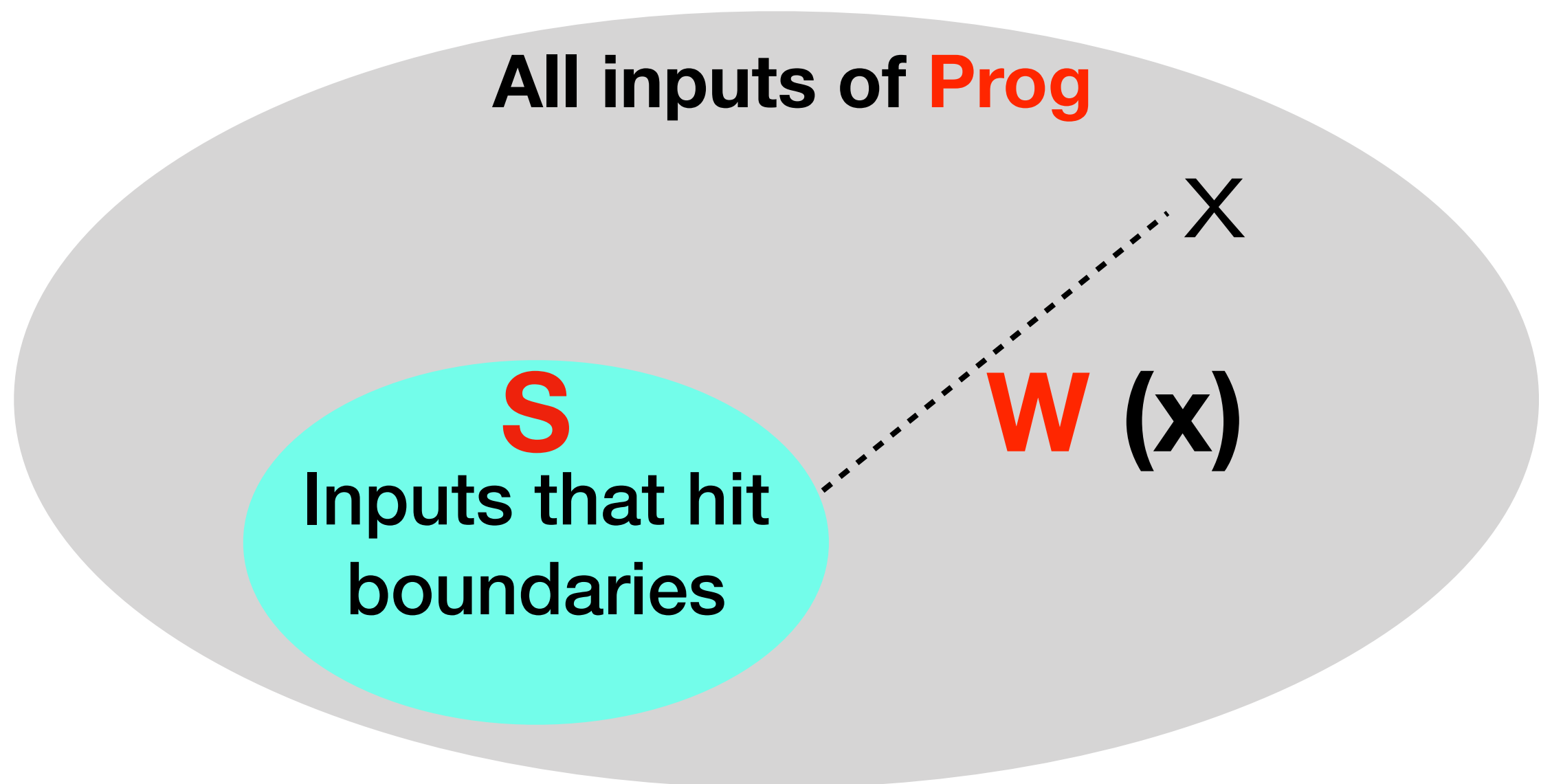
Insert  
 $w = w * \text{abs}(a - b)$

```
double w;  
void Prog_W (double x) {  
    w = w * abs(x - 1.0);  
    if (x <= 1.0) x++;  
    double y = x * x;  
    w = w * abs(y - 4.0);  
    if (y <= 4.0) x--;  
}  
double W (double x) {  
    w = 1; Prog_W(x); return w;  
}
```

**Property 1.**  $W(x) \geq 0$

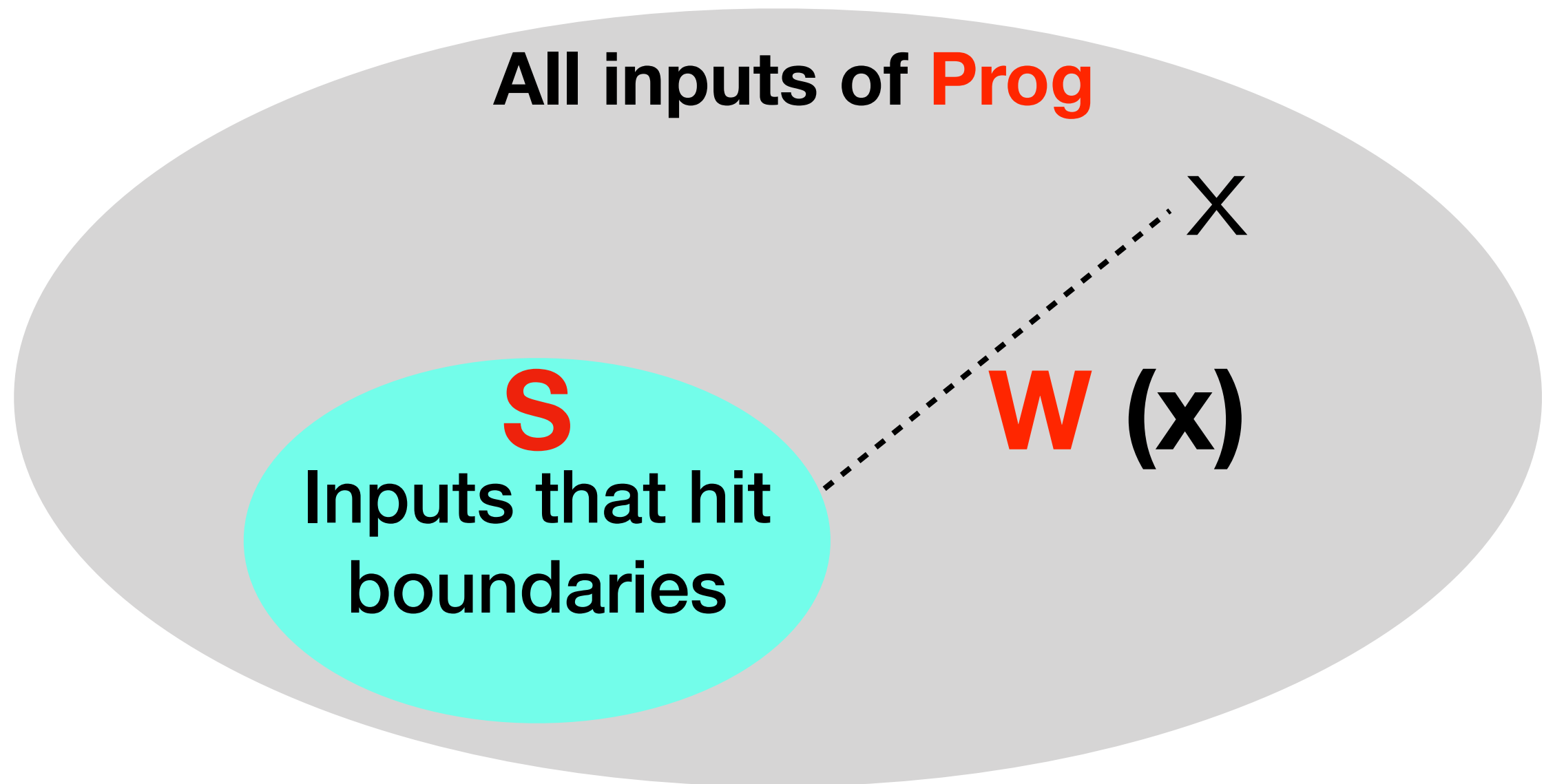
**Property 2.**  $W(x) = 0$  if and only if  $x$  is a boundary input

# Boundary value analysis as a search problem



- Search an element of **S** among all inputs of **Prog**
- Minimize **W** as mathematical optimization,  
looking for 0

# Introducing the weak distance



- **W(x)** is non-negative
- **W(x) = 0** if and only if **x** reaches **S**

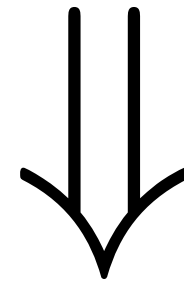
Get the weak distance **W** from the syntax of **Prog**

# Generalization

**S**

## Analyzing floating-point code

- FP constraint solving
- Coverage-based testing
- Path reachability
- Boundary value analysis
- Overflow detection



**W**

**Mathematical Optimization**

**Input  $x$  satisfies **S**  $\iff x$  minimizes **W****

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# The satisfiability problem

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DEMO

$$3x + 2y - z = 1$$

$$2x - 2y + 4z = -2$$

$$-x + \frac{1}{2}y - z = 0$$

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# Satisfiability solving

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**Planning**

**Invariant Generation**

**Type Checking**

**Model Based Testing**

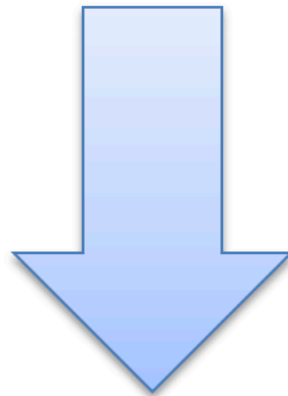
**Termination**

**...**



# Example 2

$$a > b + 2, \quad a = 2c + 10, \quad c + b \leq 1000$$



SAT

Model

$$a = 0, \quad b = -3, \quad c = -5$$

$$0 > -3 + 2, \quad 0 = 2(-5) + 10, \quad (-5) + (-3) \leq 1000$$

---

# Example 3

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$$b + 2 = c, \quad f(\text{read}(\text{write}(a, b, 3), c-2)) \neq f(c-b+1)$$

---

# Example 3 (cont)

---

$$b + 2 = c, \quad f(\text{read}(\text{write}(a, b, 3), c-2)) \neq f(c-b+1)$$

Arithmetic

---

# Example 3 (cont)

---

$$b + 2 = c, \quad f(\text{read}(\text{write}(a, b, 3), c-2)) \neq f(c-b+1)$$

Array Theory

---

# Example 3 (cont)

---

$$b + 2 = c, \quad f(\text{read}(\text{write}(a, b, 3), c-2)) \neq f(c-b+1)$$

Uninterpreted  
Functions

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# Example 3 (cont)

---

$$b + 2 = c, \quad f(\text{read}(\text{write}(a, b, 3), c-2)) \neq f(c-b+1)$$

---

# Example 3 (cont)

---

$$b + 2 = c, \quad f(\text{read}(\text{write}(a, b, 3), b+2-2)) \neq f(b+2-b+1)$$

---

# Example 3 (cont)

---

$$b + 2 = c, \quad f(\textit{read}(\textit{write}(a, b, 3), b)) \neq f(3)$$

**Array Theory Axiom**

$$\forall a, i, v : \textit{read}(\textit{write}(a, i, v), i) = v$$

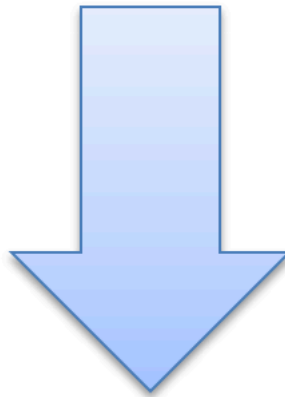


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# Example 3 (cont)

---

$$b + 2 = c, \text{ } f(3) \neq f(3)$$



UNSAT

# Floating-point Satisfiability

# Floating-point satisfiability solving in the digital age



```
Zero[] = {0.0, -0.0,};  
...  
hx = *(1+(int*)&x);  
lx = *(int*)&x;  
hy = *(1+(int*)&y);  
ly = *(int*)&y;  
sx = hx&0x80000000;  
hx ^=sx;  
hy &= 0x7fffffff;  
  
if((hy|ly)==0 || (hx>=0x7ff00000) ||  
    ((hy|((ly|-ly)>>31))>0x7ff00000))  
    return (x*y)/(x*y);  
if(hx<=hy) {  
    if((hx<hy) || (lx<ly)) return x;  
    if(lx==ly)  
        return Zero[(unsigned)sx>>31];  
}  
  
if(hx<0x00100000) {  
    if(hx==0) {  
        for (ix = -1043, i=lx; i>0; i<=1) ix -=1;
```



# Where challenges lie

Solving constraints with:

- **floating-point** arithmetic
- **non-linear** properties
- **external** functions, such as SIN, LOG, EXP

# An example of solving floating-point constraints

Find a floating-point  $x$  to satisfy

$$(SIN(x) == x) \wedge (x \geq 10^{-10})$$

Existing solutions would not solve it

Solvers of **Reals** cannot solve this constraint

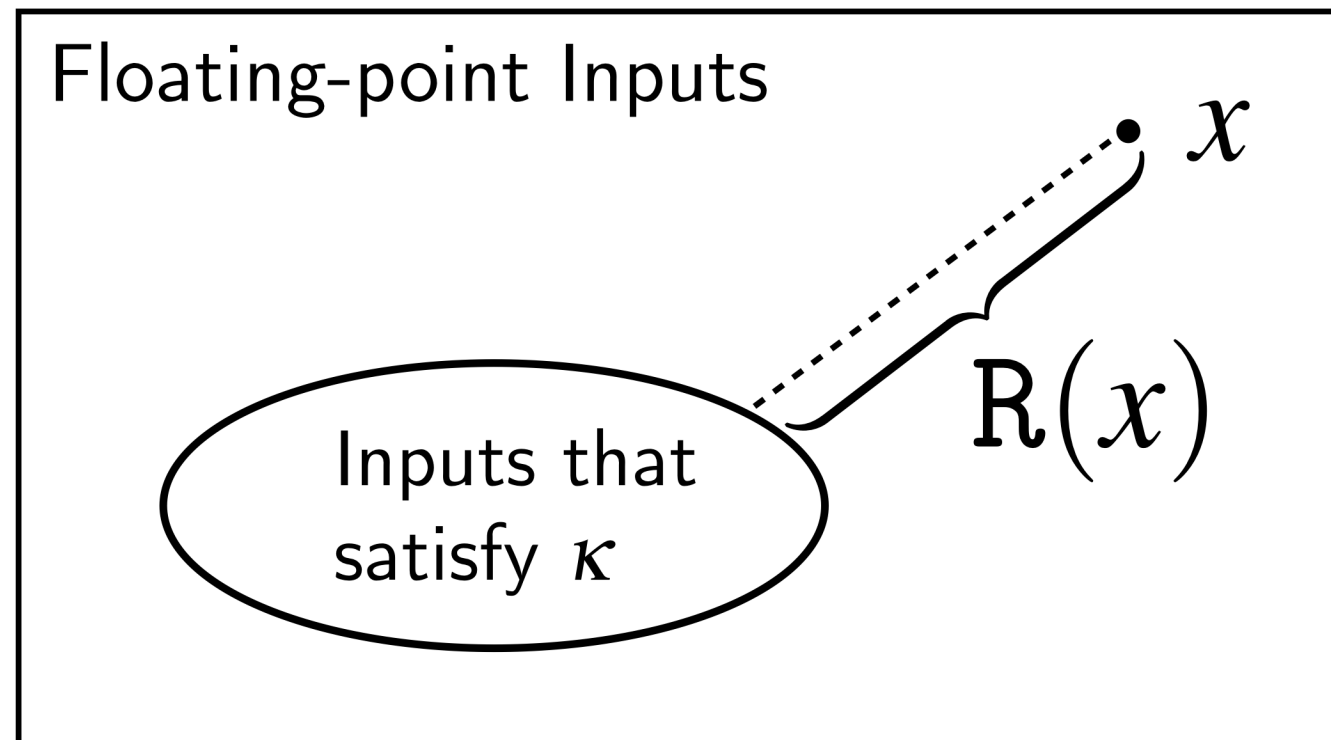
$$\text{If } x \in \mathbb{R}, SIN(x) = x \Leftrightarrow x = 0$$

Reducing to boolean satisfiability (bit-blasting) would require semantics approximation.

“IEEE-754 contains recommendations for trigonometric functions and exponentials but neither are mandated. The accuracy of implementations of these functions vary significantly, making it very hard to come up with logical models that are widely applicable. . .”

[Ref] Brain et al., “An automatable formal semantics for IEEE-754 floating-point arithmetic.” In Computer Arithmetic 2015

# Approach with Mathematical Optimisation



Step 1: Represent constraint  $\kappa$  by a function  $R$

- ▶  $R(x) \geq 0$  for all  $x$
- ▶  $R(x) = 0 \Leftrightarrow x \models \kappa$

Step 2: Minimize  $R$

Theoretical guarantee:  $\kappa$  satisfiable  $\Leftrightarrow R(x^*) = 0$   
where  $x^*$  is a minimum point

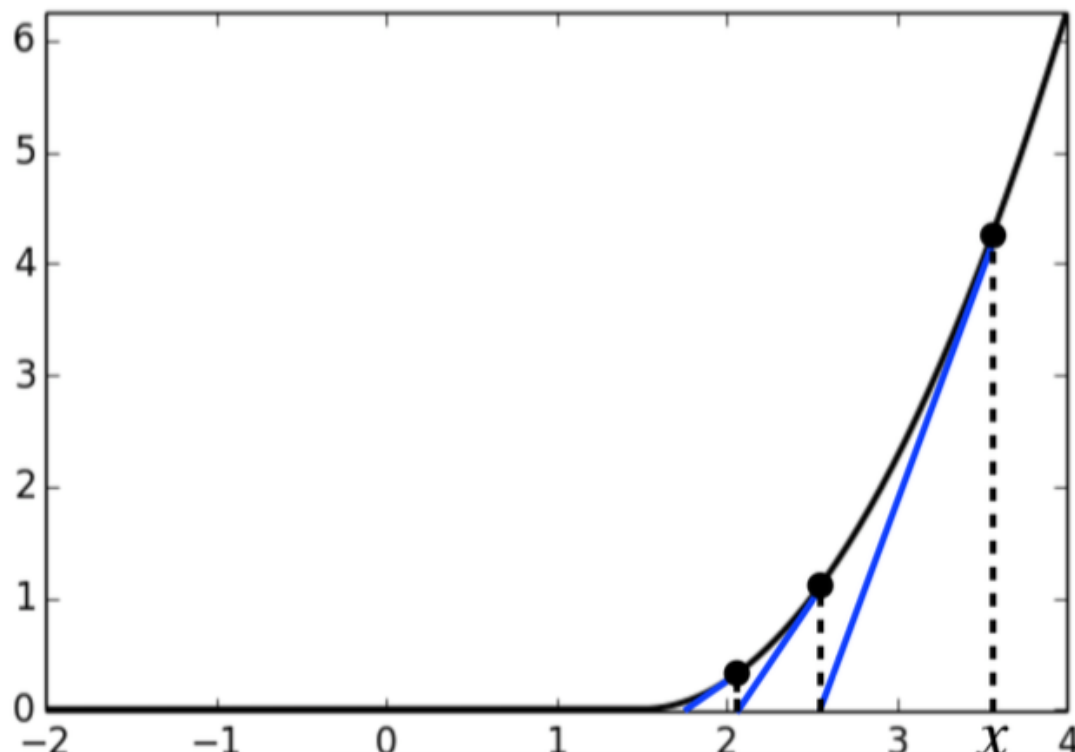
## Example $\kappa_1$

$$x \leq 1.5$$

Step 1. Transform  $\kappa_1$  to

$$R_1(x) \stackrel{\text{def}}{=} \begin{cases} 0 & \text{if } x \leq 1.5 \\ (x - 1.5)^2 & \text{otherwise} \end{cases}$$

Step 2. Minimize  $R_1$  (local optimization)



- $x^*$  can be anything  $\leq 1.5$
- $R_1(x^*) = 0 \implies x^* \models R_1$

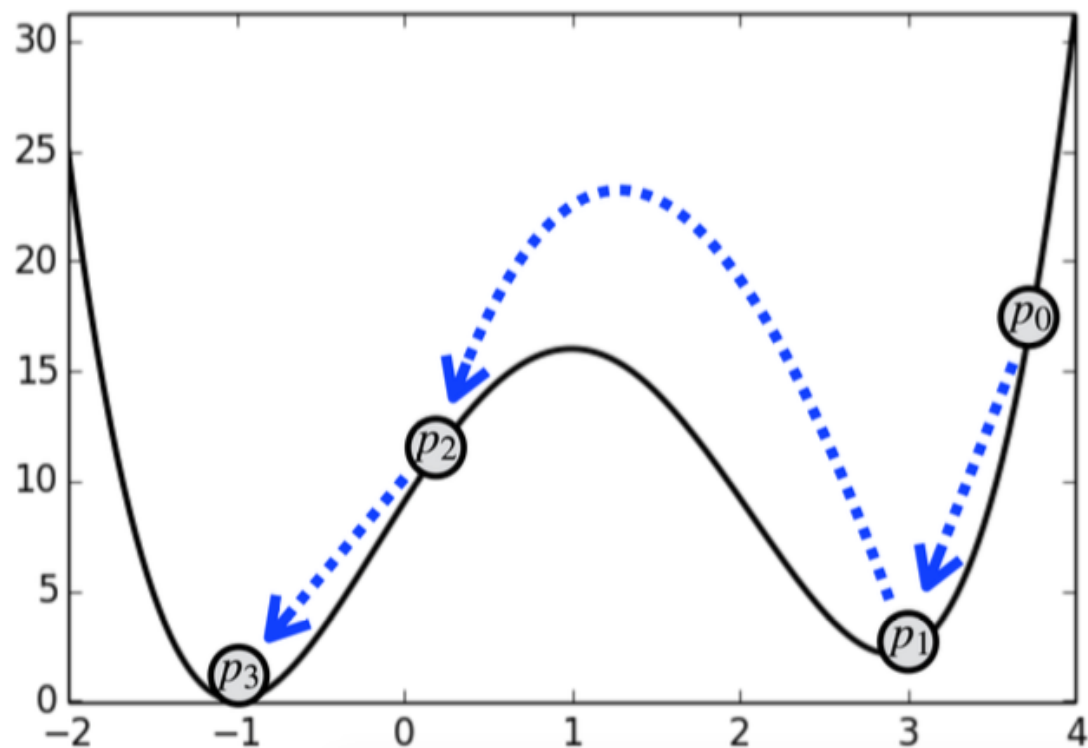


**Example  $\kappa_2$**   $(x - 1)^2 == 4 \wedge x \leq 1.5$

Step 1. Transform  $\kappa_2$  to  $R_2$

$$((x - 1)^2 - 4)^2 + \begin{cases} 0 & \text{if } x \leq 1.5 \\ (x - 1.5)^2 & \text{otherwise} \end{cases}$$

Step 2. Minimize  $R_2$  (Basinhopping)



- $x^* = -1$
- $R_2(x^*) = 0 \implies x^* \models R_2$



**Example  $\kappa_3$**   $SIN(x) == x \wedge x \geq 10^{-10}$

Step 1. Transform  $\kappa_3$  to  $R_3$ :

$$(SIN(x) - x)^2 + \begin{cases} 0 & \text{if } x \geq 10^{-10} \\ (x - 10^{-10})^2 & \text{otherwise} \end{cases}$$

Step 2. Minimize  $R_3$  (Basinhopping)

- $x^* = 9.0 * 10^{-9}$  (can be others)
- $R_3(x^*) = 0 \implies x^* \models R_3$



# Construct $R$ systematically

Constraint $\kappa$	Program $R$
$x == y$	$(x - y)^2$
$x \leq y$	$x \leq y ? 0 : (x - y)^2$
$\kappa_1 \wedge \kappa_2$	$R_1 + R_2$
$\kappa_1 \vee \kappa_2$	$R_1 * R_2$

Constraint $\kappa$	Program $R$
$x == y$	$(x - y)^2$
$x \leq y$	$x \leq y ? 0 : (x - y)^2$
$\kappa_1 \wedge \kappa_2$	$R_1 + R_2$
$\kappa_1 \vee \kappa_2$	$R_1 * R_2$

## Theoretical guarantee and limitation

- In theory,  $\kappa$  is satisfiable  $\Leftrightarrow R(x^*) = 0$
- In practice,  $R(x^*)$  may be inaccurate

# Path reachability

F00: Program under test

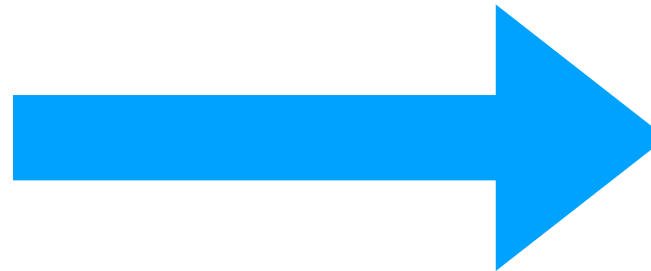
```
double square(double x){  
    return x * x;}  
void F00(double x){  
     $l_0$ : if (x <= 1) x++;  
        double y = square(x);  
     $l_1$ : if (y == 4) ... ;}
```

**Goal: Search inputs that reach the path**  
**“L0-true, L1-true”**

# Construct a weak distance

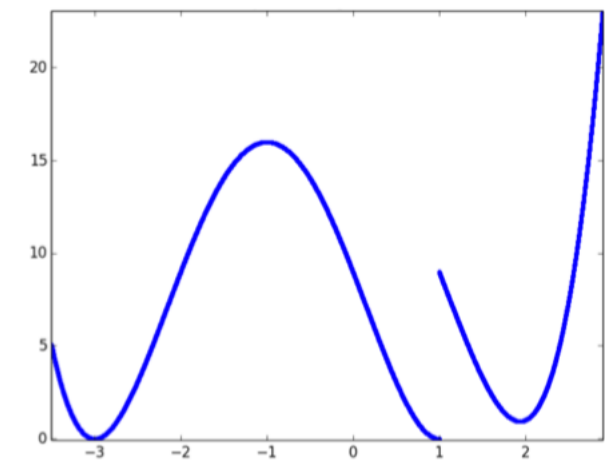
F00: Program under test

```
double square(double x){  
    return x * x;}  
void F00(double x){  
    l0: if (x <= 1) x++;  
        double y = square(x);  
    l1: if (y == 4) ... ;}
```



```
double r;  
void F00_I(double x){  
    r = r + (x ≤ 1) ? 0 : (x - 1)2;  
    l0: if (x <= 1) x++;  
        double y = square(x);  
    r = r + (y - 4)2;  
    l1: if (y == 4) ... ;}
```

```
double F00_R(double x){  
    r = 0; F00_I(x); return r;}  
}
```



Quiz: F00\_R is a weak distance iff. \_\_\_\_

DEMO: /Users/zhfu/Google Drive/active/19\_teaching\_asa/python/demo4.py

# Overflow Detection

## GNU Scientific Library's `bessel` function

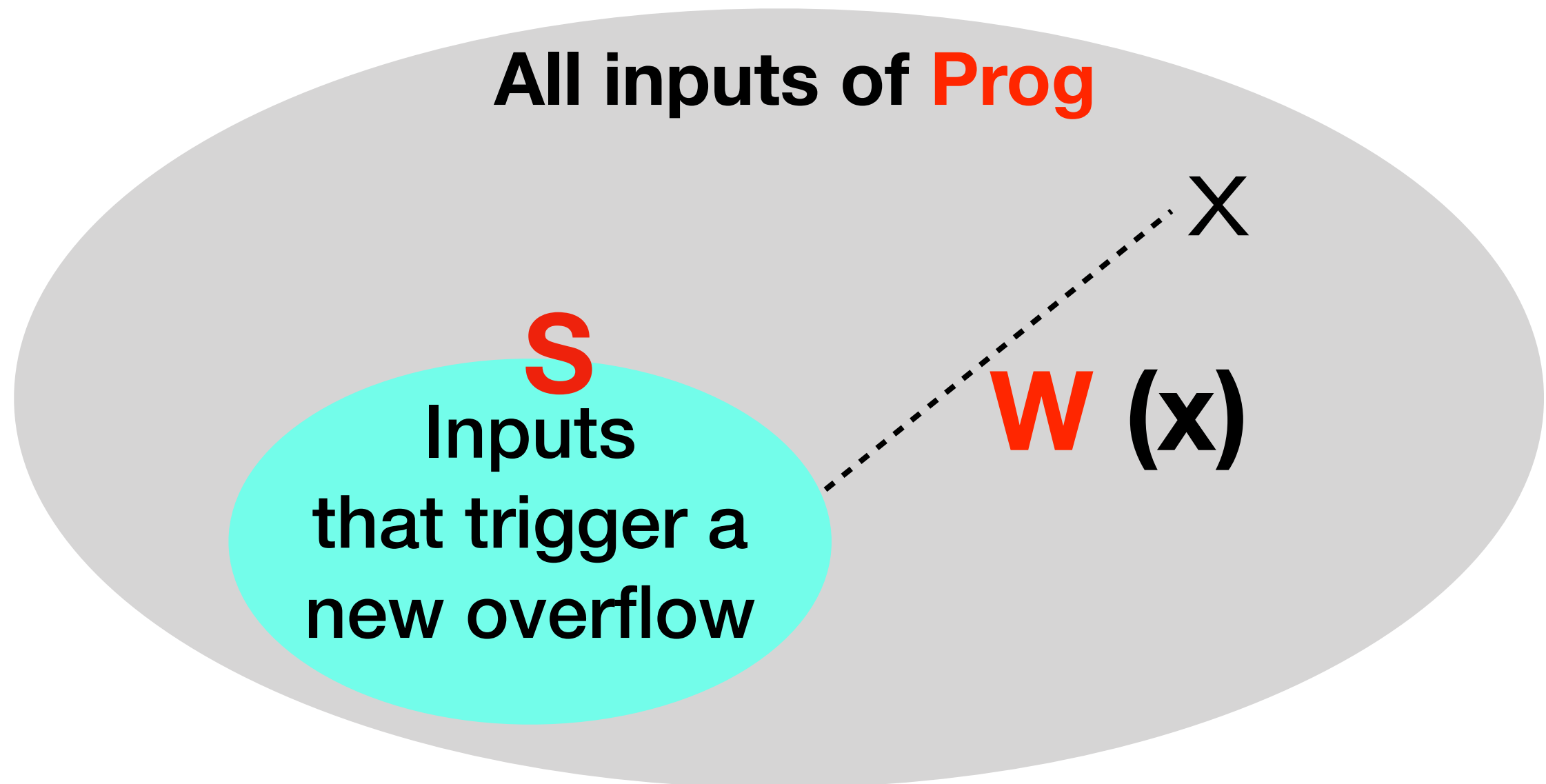
```
int gsl_sf_bessel_Knu_scaled_asymptx_e(const double nu,  
const double x, gsl_sf_result* result) {  
    double mu = 4.0 * nu * nu;  
    double mum1 = mu - 1.0;  
    double mum9 = mu - 9.0;  
    double pre = sqrt(M_PI / (2.0 * x));  
    double r = nu / x;  
    result->val = pre * (1.0 + mum1 / (8.0 * x) +  
                        mum1 * mum9 / (128.0 * x * x));  
    result->err = 2.0 * GSL_DBL_EPSILON *  
        fabs(result->val) + pre * fabs(0.1 * r * r * r);  
    return GSL_SUCCESS;  
}
```

LLVM IR

$l_1: t = 4.0 * nu$   
 $l_2: mu = t * nu$

**Goal: Trigger FP overflow for the first statement**

# Overflow detection via weak distance minimization



## Step 1. Construct **W**

- Non-negative for all  $x$
- $W = 0$  if and only if  $x$  reaches **S**

## Step 2. Minimize **W** repeatedly until $> 0$

```
Program_after_insertion (const double nu,...)
{
```

```
  l1: t = 4.0 * nu
```

```
  if (l1 is not in L) w = |t| < MAX? MAX - |t| : 0
```

L: Overflowed instructions

```
  l2: mu = t * nu
```

```
  if (l2 is not in L) w = |mu| < MAX? MAX - |mu| : 0
```

## Round 1

nu	w
0	Max
⋮	⋮
$\frac{1}{8}\sqrt{\text{Max}}$	$\frac{15}{16}\text{Max}$
$\frac{1}{4}\sqrt{\text{Max}}$	$\frac{3}{4}\text{Max}$
$\frac{1}{2}\sqrt{\text{Max}}$	0

## Round 2

nu	w
0	Max
⋮	⋮
$\frac{1}{16}\text{Max}$	$\frac{3}{4}\text{Max}$
$\frac{1}{8}\text{Max}$	$\frac{1}{2}\text{Max}$
$\frac{1}{4}\text{Max}$	0



# Summary: Weak-distance minimization

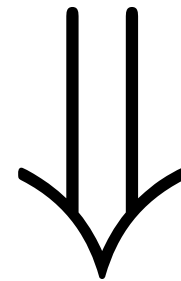
- + A **general** method
- + Do not analyze the FP code; **minimize** another one
- + **Theoretical guarantee**
- Minimizing is inherently **incomplete**  
(see exercises)

# Conclusions

**S**

## Analyzing floating-point code

- FP constraint solving
- Coverage-based testing
- Path reachability
- Boundary value analysis
- Overflow detection



**W**

**Mathematical Optimization**

**Input  $x$  satisfies **S**  $\iff$   $x$  minimizes **W****