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# **Data Types for Differential Equations**

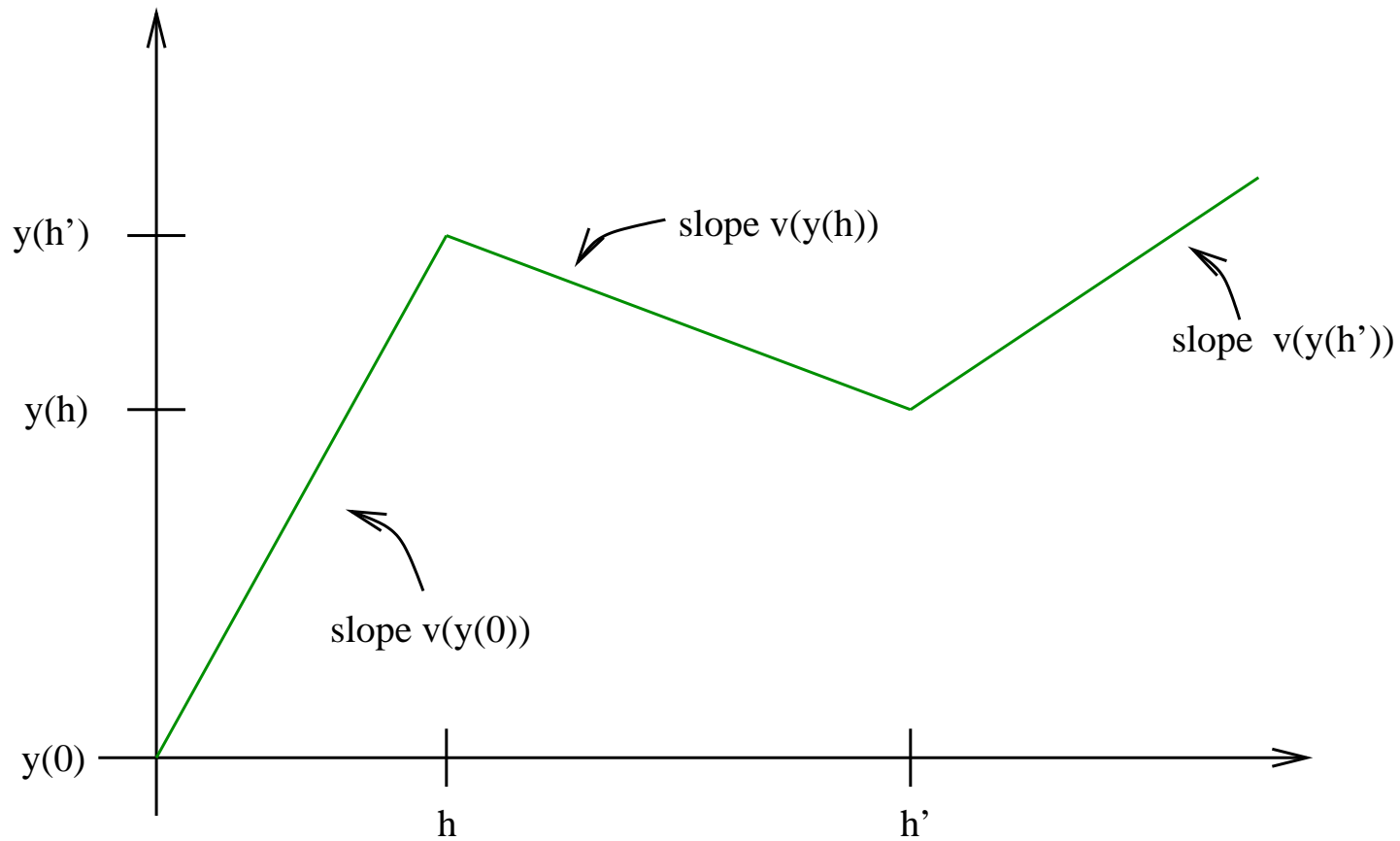
**or: functional programming over mathematical structures**

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# Conventional Techniques: Euler Polygons

**Example.**  $y' = v(y), y(0) = y_0$



# Taylor Series

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**Given.**  $y' = v(y)$ ,  $y(0) = y_0$  and a partition  $(p_0, \dots, p_k)$  with  $\Delta_i = p_i - p_{i-1}$

**First Order Approximations** (really the mean value theorem): error  $\mathcal{O}(\Delta_i)$

$$y(p_i) = y(p_{i-1}) + \Delta_i \cdot y'(\xi) \quad (\Delta_i = p_i - p_{i-1}, \xi \in [p_i, p_{i-1}])$$

$$y(p_i) \approx y(p_{i-1}) + \Delta_i \cdot v(y(p_{i-1}))$$

**Data Types.** `float` :- (or intervals :-) and representation of primitive functions

**Second Order Approximations** (really Taylor's theorem): error  $\mathcal{O}(\Delta_i^2)$

$$y(p_i) = y(p_{i-1}) + \Delta_i \cdot y'(p_i) + \frac{\Delta_i^2}{2} y''(\xi)$$

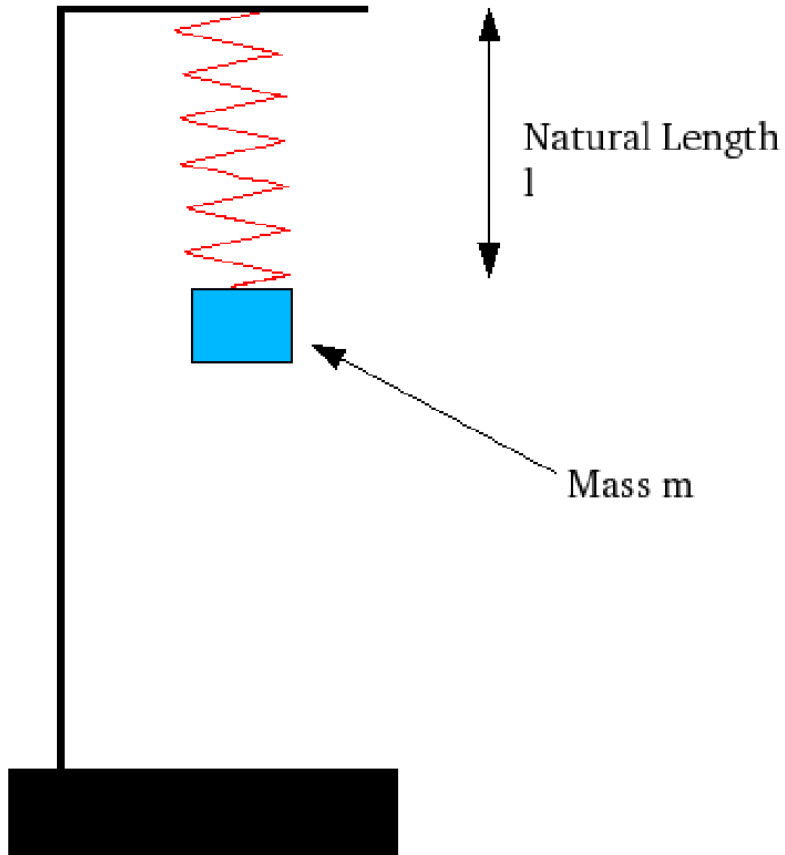
$$y(p_i) \approx y(p_{i-1}) + \Delta_i \cdot v(y(p_{i-1})) + \frac{\Delta_i^2}{2} v' \cdot v(y(p_{i-1}))$$

**Data Types.** Primitive functions *and their derivatives*

**Modularity.** Derivatives of compound functions via chain rule

# The Mass on a Spring Problem

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## Two regimes of Evolution:

- $y \leq l$ : Gravity
- $y \geq l$ : Gravity plus Hooke's law

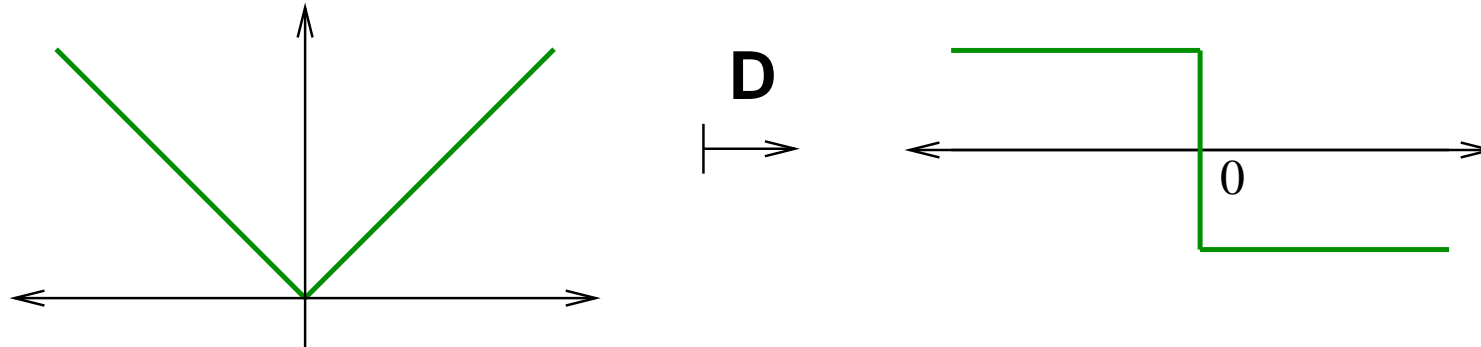
## As a Differential Equation.

$$y'' = \begin{cases} g - \frac{k}{m}y & y \geq 0 \\ g & y \leq 0 \end{cases}$$

**Crucially.** The (function defining the) differential equation is *Lipschitz*, but *not*  $C^1$ .

# But Derivatives can be Sandwiched

**Example.** Absolute value  $f(x) = |x|$



**Example.**  $f(x, y) = \max(x, y)$

$$D(f)(x, y) = \begin{cases} (1, 0) & x > y \\ [0, 1] \times [0, 1] & x = y \\ (0, 1) & x < y \end{cases}$$

**New Data Types.** Derivatives (and, *a posteriori*, functions) are *interval valued*.

- what is the *mathematical theory* of interval derivatives?
- how about *convergence speed* and relation to conventional methods?

# Main Ideas

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**Goal.** Use of *higher order* methods  $\rightsquigarrow$  *much* improved convergence behaviour

## Main Idea.

- trade the *real line*  $\mathbb{R}$  for the *interval domain*  $\mathbf{IR} = \{[a, b] \mid a, b \in \mathbb{R}, a \leq b\}$
- trade *classical* for *domain theoretic* (Clarke's) derivatives

## Digression. Domain Theoretic Differential Calculus

- Taylor's Theorem
- the Chain Rule

## Buy one, get one free – and some more goodies

- two orders (of differentiability) for the price of one
- plus: guaranteed (much improved) error bounds
- plus: “proof-by-calculation”-style existence assertions

# Domain Theoretic Differential Calculus

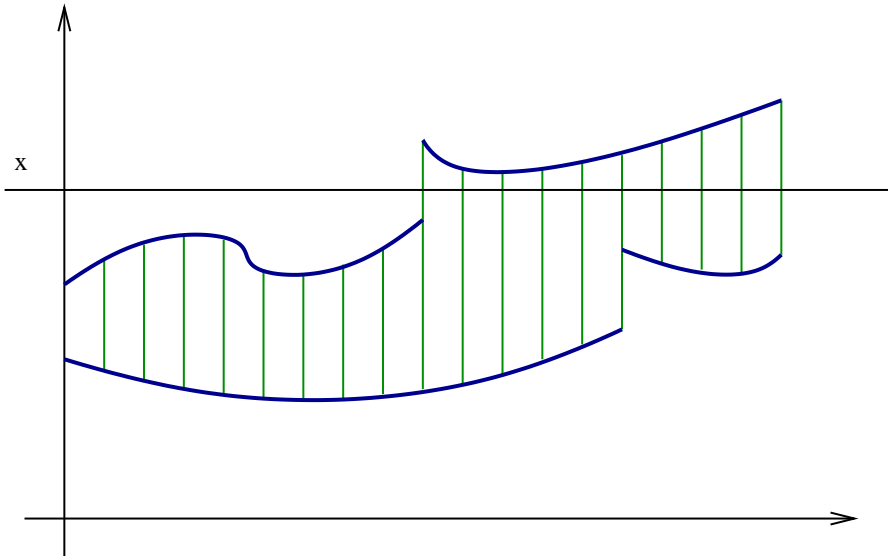
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**Outset.** Consider functions  $f = [\underline{f}, \overline{f}] : O \rightarrow \mathbf{IR}$  where

- $O \subseteq \mathbb{R}^n$  is (usually) open
- $(\mathbf{IR}, \sqsubseteq)$  is the *interval domain* of compact intervals ordered by reverse inclusion

**Topology.** Consider  $\mathbf{IR}$  as equipped with the *Scott topology* so that

$$f \text{ continuous} \iff \underline{f}, \overline{f} \text{ upper (lower) semi continuous}$$



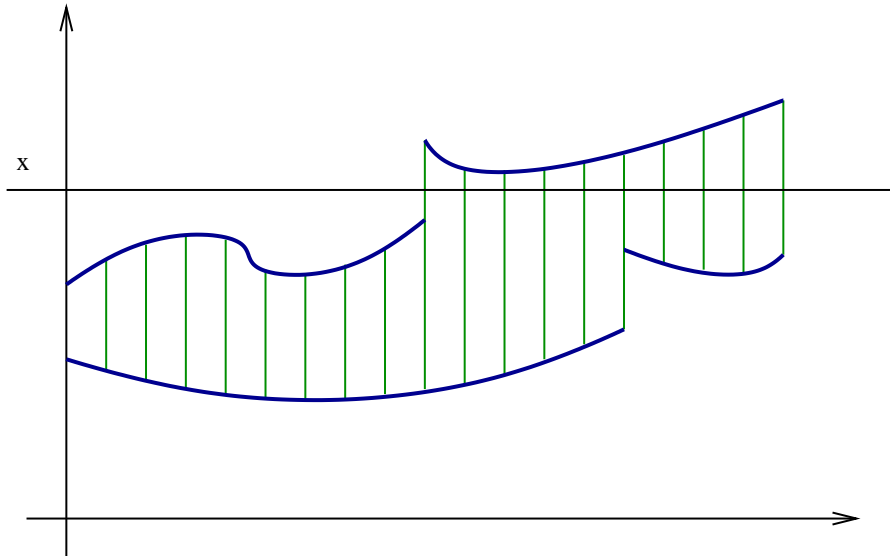
# Domain Theoretic Differential Calculus

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**Example.** Intermediate Value Theorem.

If  $f : [a, b] \rightarrow \mathbf{IR}$  is continuous and

$$x \in f(a) \sqcap f(b)$$

then  $x \in f(t)$  for some  $t \in [a, b]$ .

# The Domain Theoretic Derivative

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## Informal Definition.

Suppose  $f : O \rightarrow \mathbb{R}$  and  $a \subseteq O \subseteq \mathbb{R}$  are open.

$$D_a(f) = \bigsqcap_{x \neq y \in a} \frac{f(y) - f(x)}{y - x} \qquad D(f)(x) = \bigsqcup_{x \in a} D_a(x)$$

**Idea.**  $D(f)(x)$  contains all slopes that appear around  $x$ .

## Formal Definition.

Suppose  $f : O \rightarrow \mathbb{R}$  and  $O \subseteq \mathbb{R}^n$  is open.

Then  $f$  has a Lipschitz constant  $b \in \mathbf{IR}^n$  around the open set  $a \subseteq O$ , written

$$f \in \delta(a, b) \text{ iff } \forall x, y \in a. b(x - y) \sqsubseteq f(x) - f(y)$$

and the *Domain Theoretic Derivative* is the sup of all Lipschitz constants

$$D(f) = \bigsqcup_{f \in \delta(a, b)} a \searrow b \quad \text{where } a \searrow b(x) = b \text{ if } x \in a \text{ and } (-\infty, \infty) \text{ otherwise}$$

# Some Properties

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**Existence and Continuity.**  $D(f)$  is Scott continuous and  $D(f) = f'$  if  $f \in \mathcal{C}^1$ .

## Relationship to Clarke's Gradient

- $D(f)$  is the “smallest rectangular approximation” of Clarke's gradient
- equality if we work with compact sets rather than products of intervals

## Examples.

- $f(x) = |x| \rightsquigarrow D(f)(0) = [-1, 1]$  as expected
- $f(x) = \sqrt{|x|} \rightsquigarrow D(f)(0) = \perp$

**More generally.**  $D(f)(x) \neq \perp$  whenever  $f$  is Lipschitz in a neighbourhood of  $x$ .

$\rightsquigarrow$  locally Lipschitz vector fields (also guarantees uniqueness)

# The Chain Rule

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## Notation

- If  $f = (f_1, \dots, f_k) : O \rightarrow \mathbb{R}^k$  then  $D(f) = (D(f_1), \dots, D(f_k))$
- If  $f : O \rightarrow \mathbb{R}^m$  and  $g : P \rightarrow \mathbb{R}^n$  for  $O \subseteq \mathbb{R}^n$  with  $g(x) \subseteq O$

$$f \circ g(x) = \prod_{y \in g(x)} f(y)$$

## The Chain Rule.

If  $f : O \rightarrow P$  and  $g : P \rightarrow \mathbb{R}^k$  where  $O \subseteq \mathbb{R}^n$  and  $P \subseteq \mathbb{R}^m$  are open, then

$$D(f \circ g) \supseteq D(f) \circ g \cdot D(g)$$

**Equality may fail:** Suppose  $f(x) = |x|$  and  $g(x) = \max(x, 0)$ . Then

$$D(f \circ g)(0) = D(g)(0) = [0, 1]$$

$$D(f) \circ g \cdot D(g)(0) = [-1, 1] \cdot [0, 1] = [-1, 1]$$

(“*smoothing out*”, also e.g. for  $f(x) = x^2$  and  $g(x) = |x|$ )

# The Mean Value Theorem

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## The Mean Value Theorem.

Suppose  $f : [a, b] \rightarrow \mathbb{R}$  is *continuous* and  $x \in [a, b]$ . Then

$$f(x) \in f(a) + (x - a)D(f)(\xi)$$

for some  $\xi \in [a, x]$ .

**Taylor's Theorem.** Suppose  $f : [a, b] \in \mathcal{C}^n[a, b]$ . Then

$$f(x) \in f(a) + (x - a)f'(a) + \cdots + \frac{(x - a)^n}{n!} f^{(n)}(a) + \frac{(x - a)^{n+1}}{(n + 1)!} D(f^{(n)})(\xi)$$

for some  $\xi \in [a, x]$ .

**Remark.** Taylor's Theorem holds *even without the assumption*  $f \in \mathcal{C}^n$  if we consider derivatives of functions  $f : O \rightarrow \mathbb{R}$ .

# Back to Differential Equations ...

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**Problem.** Find a solution of the initial value problem

$$y' = v(y), y(t_0) = a$$

where  $O \subseteq \mathbb{R}^n$  is open,  $v : O \rightarrow \mathbb{R}^n$  is locally Lipschitz and  $a \in \mathbb{R}^n$ .

**Our Setup.** We start with two functions

- $u : \mathbf{IO} \rightarrow \mathbf{IR}^n$  that *extends*  $v$ , i.e.  $u(x) \sqsubseteq v(x)$  for all  $x \in O$ .
- $u' : \mathbf{IO} \rightarrow \mathbf{IR}^{n \times n}$  that *extends*  $D(v)$ , i.e.  $u'(x) \sqsubseteq D(v)(x)$  for all  $x \in O$ .

**Existence Theorem.** Suppose that  $\alpha, E \in \mathbf{IR}^n$  and

$$u(\alpha + [0, h] \cdot E) \subseteq E$$

Then, for all  $a \in \alpha$ , the problem has a solution  $z : [t_0, t_0 + h] \rightarrow \mathbb{R}^n$  that satisfies

$$z(t) \in \alpha + (t - t_0) \cdot u(\alpha + [0, h] \cdot E) \subseteq \alpha + [0, h] \cdot E$$

# Algorithmic Digression

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**Given.**  $\alpha \in \mathbb{I}\mathbb{R}^n$  so that the solution  $z$  of the IVP satisfies  $z(t') \in \alpha$

- Pick a step size  $h$
- Guess a *valid enclosure*  $E$  s.t.  $u(\alpha + [0, h] \cdot E) \subseteq E$
- Put  $y(t) = \alpha + (t' - t)u(\alpha + [0, h] \cdot E)$  for  $t \in [t', t' + h]$

Then the solution  $z$  will satisfy  $z(t) \in y(t)$  for  $t \in [t', t' + h]$ .

**Proof by Calculation.** Repeating this process for  $t = t_0, t_0 + h_0, \dots, t_0 + h_k$  gives

- a *proof of existence* of a solution in  $[t_0, t_0 + h_k]$
- guaranteed (first order) *bounds on the values* of a solution.

**Parameters to fiddle.** Enclosure  $E$  and step size  $h$ .

## Second Order Steps

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**Enclosure Theorem** (2nd Order Version) Suppose  $E$  is a valid enclosure at  $\alpha$  for time  $h$ , i.e.

$$u(\alpha + [0, h] \cdot E) \subseteq E$$

Then every solution  $z : [t_0, t_0 + h]$  of  $y' = v(y)$ ,  $y(t_0) = a \in \alpha$  satisfies

$$z(t) \in \alpha + (t - t_0)u(\alpha) + \frac{(t - t_0)^2}{2}u' \cdot u(\alpha + [0, h] \cdot E)$$

*Proof.* Chain Rule and Taylor's Theorem.

Compare with *first order approximation*:

$$z(t) \in \alpha + (t - t_0)u(\alpha + [0, h] \cdot E)$$

- overestimation is *quadratic*
- significant gain *in practice*, but *not in theory*

# Comparison

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**Under the Carpet:** Intricacies of Guessing, Monotonicity and Assembly of Solutions

**Informal Notation.** Let  $y_1(\mathcal{P})$  (resp.  $y_2(\mathcal{P})$ ) denote the gluing together of  $k$  first (second) order steps.

**Monotonicity.** If  $\mathcal{Q}$  is a refinement of  $\mathcal{P}$ , then  $y_i(\mathcal{P}) \sqsubseteq y_i(\mathcal{Q})$ ,  $i = 1, 2$ .

(guessing for a finer partition improves guessing for a coarser partition)

**Convergence.** If  $(\mathcal{P}_k)$  is a sequence of partitions that refines exponentially fast, then  $y_i(\mathcal{P}_k) \rightarrow z$  exponentially fast, where  $z(t_0) = a$ ,  $z' = v(z)$ .

**Striking Fact.** Cannot *prove* that 2nd order converges faster.

- if  $D(v)$  is bounded by  $L$ , then  $nL$  is a Lipschitz constant for  $v$
- first order convergence also depends on Lipschitz constant, and
- 2nd order convergence speed is a *global* estimate

# Types, Concretely

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**Vector Fields:** symbolic representation

```
data Term = Plus Term Term | ... | Max Term Term | Abs Term
```

(Dependent Types would be nice to have)

**Evaluation.**

```
eval :: Term -> Vector -> Interval
```

```
eval (Plus s t) v = iadd (eval s v) (eval t v)
```

```
eval (Max s t) v = imax (eval s v) (eval t v)
```

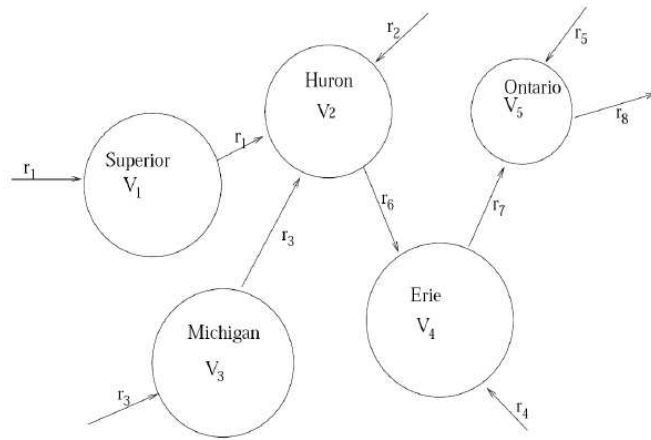
**Differentiation.** Symbolically, e.g.

```
deriv :: Term -> Vector -> Vector
```

(using the chain rule)

# Experimental Results: Differentiable Vector Fields

**Lake Pollution Model** (restricted to Lake Huron, Michigan and Superiour)



| Stepsize | Width               |                     | Run Time            |                     | Markup |
|----------|---------------------|---------------------|---------------------|---------------------|--------|
|          | 1 <sup>st</sup> Ord | 2 <sup>nd</sup> Ord | 1 <sup>st</sup> Ord | 2 <sup>nd</sup> Ord |        |
| 0.1      | 1.36                | 0.0684              | 0.57                | 0.45                | 200    |
| 0.01     | 0.0367              | 0.0000184           | 9.2                 | 4.63                | 2000   |
| 0.001    | 0.00301             | 0.0000002           | 98.9                | 57.4                | 15060  |

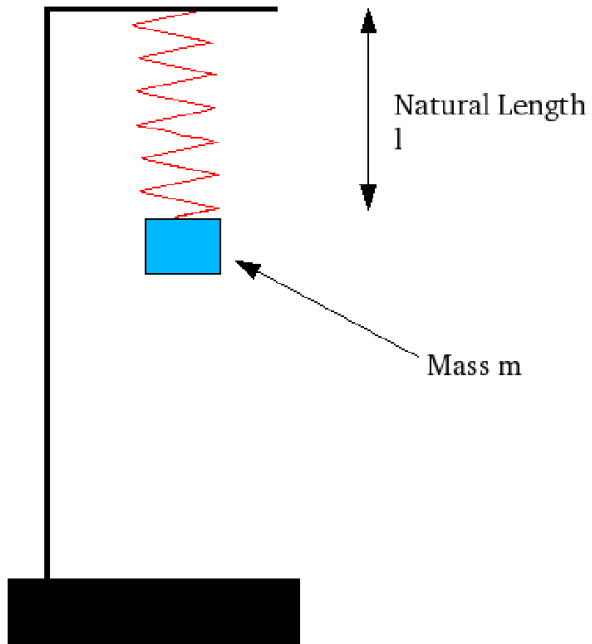
Accuracy at  $t = 10$

Decline of Pollution in the network of Great Lakes in North America over time

$$v(y_1, y_2, y_3) = \left( -\frac{r_1}{V_1}y_1, \frac{r_1}{V_1}y_1 + \frac{r_3}{V_3}y_3 - \frac{r_1 + r_2 + r_3}{V_2}y_2, -\frac{r_3}{V_3}y_3 \right)$$

**Note.** The second order method is not only *better* but also *faster*!

# Mass on a Spring



| Stepsize | Width               |                     | Run Time            |                     | Markup |
|----------|---------------------|---------------------|---------------------|---------------------|--------|
|          | 1 <sup>st</sup> Ord | 2 <sup>nd</sup> Ord | 1 <sup>st</sup> Ord | 2 <sup>nd</sup> Ord |        |
| 0.01     | 1105                | 42                  | 32.3                | 2                   | 26.3   |
| 0.001    | 212                 | 0.38                | 2610                | 61                  | 557    |

Accuracy at  $t = 8$

$$v(y_1, y_2) = (y_2, -\max(-g, \frac{k}{m}x - g))$$

Initial values:  $y_1 = y_2 = 0$

# Some Conclusions

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## Implementation is Important.

- also uncovers mathematically interesting questions
- reveals unexpected phenomena
- identifies shortcomings of the theory

## Conventional Techniques.

- require *existence* of classical derivatives
- no guaranteed bounds

## Calculus in Domain Theory.

- uses *generalised* derivatives that *always exist*
- automatic *existence proof* as a by-product