

# Simple essence of AD

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# Definition of Derivative

## Definition

Let  $f : \mathbb{R} \rightarrow \mathbb{R}$  be a function. The derivative of  $f$  at point  $x \in \mathbb{R}$  is defined the following way:

$$f'(x) = \lim_{\varepsilon \rightarrow 0} \frac{f(x + \varepsilon) - f(x)}{\varepsilon}$$

This definition will also work with functions of types  $\mathbb{C} \rightarrow \mathbb{C}$  and  $\mathbb{R} \rightarrow \mathbb{R}^n$ .

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# Definition of Derivative

For functions  $F$  of types  $\mathbb{R}^m \rightarrow \mathbb{R}$  and  $\mathbb{R}^m \rightarrow \mathbb{R}^n$  (with  $n > 1$ ), we need a different definition.

- For functions of type  $\mathbb{R}^m \rightarrow \mathbb{R}$ , it is necessary the introduction of the notion of partial derivatives,  $\frac{\partial F}{\partial x_j}$ , with  $j \in \{1, \dots, m\}$ .
- For functions of type  $\mathbb{R}^m \rightarrow \mathbb{R}^n$  (with  $n > 1$ ), apart from the use of partial derivatives, it is necessary the use of Jacobian matrices  $\mathbf{J}_{i,j} = \frac{\partial F_i}{\partial x_j}$ , where  $i \in \{1, \dots, n\}$  and  $F_i$  is a function  $\mathbb{R}^m \rightarrow \mathbb{R}$ .

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# Generalization and Chain Rule

Let **A** and **B** be two Jacobian matrices.  
The composition rule in  $\mathbb{R}^m \rightarrow \mathbb{R}^n$  is:

$$(\mathbf{A} \cdot \mathbf{B})_{i,j} = \sum_{k=1}^m \mathbf{A}_{i,k} \cdot \mathbf{B}_{k,j}$$



# Generalization and Chain Rule

Assuming that the notion of derivatives that we need matches with a linear map, where it is accepted the composition rule previously seen, we will define a new generalization:

$$\begin{aligned} \lim_{\varepsilon \rightarrow 0} \frac{f(x + \varepsilon) - f(x)}{\varepsilon} - f'(x) = 0 &\Leftrightarrow \lim_{\varepsilon \rightarrow 0} \frac{f(x + \varepsilon) - (f(x)) + \varepsilon \cdot f'(x)}{\varepsilon} = 0 \\ &\Leftrightarrow \lim_{\varepsilon \rightarrow 0} \frac{\|f(x + \varepsilon) - (f(x)) + \varepsilon \cdot f'(x)\|}{\|\varepsilon\|} = 0 \end{aligned}$$

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# Derivate as a linear map

## Definition

Let  $f :: a \rightarrow b$  be a function, where  $a$  and  $b$  are vectorial spaces that share a common underlying field. The first derivative definition is the following:

$$\mathcal{D} :: (a \rightarrow b) \rightarrow (a \rightarrow (a \multimap b))$$

If we differentiate two times, we have:

$$\mathcal{D}^2 = \mathcal{D} \circ \mathcal{D} :: (a \rightarrow b) \rightarrow (a \rightarrow (a \multimap a \multimap b))$$

# Rules for Differentiation - Sequential Composition

## Theorem

*Let  $f :: a \rightarrow b$  and  $g :: b \rightarrow c$  be two functions. Then the derivative of the composition of  $f$  and  $g$  is:*

$$\mathcal{D} (g \circ f) a = \mathcal{D} g (f a) \circ \mathcal{D} f a$$

# Rules for Differentiation - Sequential Composition

Unfortunately the previous theorem isn't a efficient recipe for composition. As such we will introduce a second derivative definition:

$$\begin{aligned}\mathcal{D}_0^+ &:: (a \rightarrow b) \rightarrow ((a \rightarrow b) \times (a \rightarrow (a \multimap b))) \\ \mathcal{D}_0^+ f &= (f, \mathcal{D} f)\end{aligned}$$

With this, the chain rule will have the following expression:

$$\begin{aligned}\mathcal{D}_0^+ (g \circ f) & \\ \{\text{definition of } \mathcal{D}_0^+\} & \\ = (g \circ f, \mathcal{D} (g \circ f)) & \\ \{\text{theorem and definition of } g \circ f\} & \\ = (\lambda a \rightarrow g(f a), \lambda a \rightarrow \mathcal{D} g (f a) \circ \mathcal{D} f a) &\end{aligned}$$

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# Rules for Differentiation - Sequential Composition

Having in mind optimizations, we introduce the third and last derivative definition:

$$\begin{aligned}\mathcal{D}^+ &:: (a \rightarrow b) \rightarrow (a \rightarrow (b \times (a \multimap b))) \\ \mathcal{D}^+ f a &= (f a, \mathcal{D} f a)\end{aligned}$$

As  $\times$  has more priority than  $\rightarrow$  and  $\multimap$ , we can rewrite  $\mathcal{D}^+$  as:

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# Rules for Differentiation - Sequential Composition

## Corollary

$\mathcal{D}^+$  is compositionally efficient in relation to  $(\circ)$ , that is, in Haskell:

$$\mathcal{D}^+ (g \circ f) a = \mathbf{let} \{ (b, f') = \mathcal{D}^+ f a; (c, g') = \mathcal{D}^+ g b \} \\ \mathbf{in} (c, g' \circ f')$$

$$\begin{array}{ccccc} (C \times C^B) \times B^A & \xleftarrow{\mathcal{D}^+ g \times id} & B \times B^A & \xleftarrow{\mathcal{D}^+ f} & A \\ \downarrow (id \times (uncurry (\circ))) \circ assocr & & & \swarrow \mathcal{D}^+ (g \circ f) & \\ C \times C^A & & & & \end{array}$$

# Rules for Differentiation - Parallel Composition

Another important way of combining functions is the operation cross, that combines two functions in parallel:

$$(\times) :: (a \rightarrow c) \rightarrow (b \rightarrow d) \rightarrow (a \times b \rightarrow c \times d)$$

$$f \times g = \lambda(a, b) \rightarrow (f \ a, g \ b)$$

## Theorem

*Let  $f :: a \rightarrow c$  and  $g :: b \rightarrow d$  be two function. Then the cross rule is the following:*

$$\mathcal{D}(f \times g)(a, b) = \mathcal{D}f \ a \times \mathcal{D}g \ b$$

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# Rules for Differentiation - Parallel Composition

## Corollary

*The function  $\mathcal{D}^+$  is compositional in relation to  $(\times)$*

$$\mathcal{D}^+ (f \times g) (a, b) = \mathbf{let} \{ (c, f') = \mathcal{D}^+ f a; (d, g') = \mathcal{D}^+ g b \} \\ \mathbf{in} ((c, d), f' \times g')$$

# Derivative and Linear Functions

## Definition

A function  $f$  is said to be linear when preserves addition and scalar multiplication.

$$f(a + a') = f a + f a'$$

$$f(s \cdot a) = s \cdot f a$$

## Theorem

*For all linear functions  $f$ ,  $\mathcal{D} f a = f$ .*

## Corollary

*For all linear functions  $f$ ,  $\mathcal{D}^+ f = \lambda a \rightarrow (fa, f)$ .*

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## A short introduction

- We want to calculate  $\mathcal{D}^+$ .
- However,  $\mathcal{D}$  is not computable.
- Solution: reimplement corollaries using category theory.



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# Instance deduction

Using corollaries 3.1 and 1.1 we can determine that

- (DP.1)  $\mathcal{D}^+ id = \lambda a \rightarrow (id\ a, id)$
- (DP.2)

$$\mathcal{D}^+ (g \circ f) = \lambda a \rightarrow \mathbf{let}\ \{(b, f') = \mathcal{D}^+ f\ a; (c, g') = \mathcal{D}^+ g\ b\} \\ \mathbf{in}\ (c, g' \circ f')$$

Saying that  $\hat{\mathcal{D}}$  is a functor is equivalent to, for all  $f$  and  $g$  functions of appropriate types:

$$id = \hat{\mathcal{D}}\ id = \mathcal{D}\ (\mathcal{D}^+ id)$$

$$\hat{\mathcal{D}}\ g \circ \hat{\mathcal{D}}\ f = \hat{\mathcal{D}}\ (g \circ f) = \mathcal{D}\ (\hat{\mathcal{D}}\ (g \circ f))$$

## Instance deduction

Based on (DP.1) and (DP.2) we'll rewrite the above into the following definition:

$$id = \mathcal{D} (\lambda a \rightarrow (id \ a, id))$$

$$\hat{\mathcal{D}} \ g \circ \hat{\mathcal{D}} \ f = \mathcal{D} (\lambda a \rightarrow \mathbf{let} \ \{ (b, f') = \mathcal{D}^+ \ f \ a; (c, g') = \mathcal{D}^+ \ g \ b \} \ \mathbf{in} \ (c, g' \circ f'))$$

The first equation shown above has a trivial solution.

To solve the second we'll first solve a more general one:

$$\mathcal{D} \ g \circ \mathcal{D} \ f = \mathcal{D} (\lambda a \rightarrow \mathbf{let} \ \{ (b, f') = f \ a; (c, g') = g \ b \} \ \mathbf{in} \ (c, g' \circ f'))$$

This condition also leads us to a trivial solution inside our instance.



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# Instance deduction

## $\hat{\mathcal{D}}$ definition for linear functions

$linearD :: (a \rightarrow b) \rightarrow \mathcal{D} a b$

$linearD f = \mathcal{D} (\lambda a \rightarrow (f a, f))$

## Categorical instance we've deduced

**instance** *Category*  $\mathcal{D}$  **where**

$id = linearD id$

$\mathcal{D} g \circ \mathcal{D} f =$

$\mathcal{D} (\lambda a \rightarrow \mathbf{let} \{ (b, f') = f a; (c, g') = g b \} \mathbf{in} (c, g' \circ f'))$

# Instance proof

In order to prove that the instance is correct we must check if it follows laws (C.1) and (C.2).

First we must make a concession: that we only use morfisms arising from  $\mathcal{D}^+$ . If we do, then  $\mathcal{D}^+$  is a functor.

## (C.1) proof

$$\text{id} \circ \hat{\mathcal{D}} f$$

{ functor law for id (specification of  $\hat{\mathcal{D}}$ ) }

$$= \hat{\mathcal{D}} \text{id} \circ \hat{\mathcal{D}} f$$

{ functor law for  $(\circ)$  }

$$= \hat{\mathcal{D}} (\text{id} \circ f)$$

{ categorical law }

$$= \hat{\mathcal{D}} f$$

# Instance proof

## (C.2) proof

$$\begin{aligned}
 & \hat{\mathcal{D}} h \circ (\hat{\mathcal{D}} g \circ \hat{\mathcal{D}} f) \\
 & \{ \text{2x functor law for } (\circ) \} \\
 & = \hat{\mathcal{D}} (h \circ (g \circ f)) \\
 & \{ \text{categorical law} \} \\
 & = \hat{\mathcal{D}} ((h \circ g) \circ f) \\
 & \{ \text{2x functor law for } (\circ) \} \\
 & = (\hat{\mathcal{D}} h \circ \hat{\mathcal{D}} g) \circ \hat{\mathcal{D}} f
 \end{aligned}$$

## Note

Those proofs don't require anything from  $\mathcal{D}$  and  $\hat{\mathcal{D}}$  aside from functor laws. As such, all other instances of categories created from a functor won't require further proving like this one did.

# Monoidal categories and functors

Generalized parallel composition shall be defined using a monoidal category:

**class** *Category*  $k \Rightarrow \text{Monoidal } k$  **where**

$(\times) :: (a \text{ ' } k' \text{ } c) \rightarrow (b \text{ ' } k' \text{ } d) \rightarrow ((a \times b) \text{ ' } k' \text{ } (c \times d))$

**instance** *Monoidal*  $(\rightarrow)$  **where**

$f \times g = \lambda(a, b) \rightarrow (f \text{ } a, g \text{ } b)$

## Monoidal Functor definition

A monoidal functor  $F$  between categories  $\mathcal{U}$  and  $\mathcal{V}$  is such that:

- $F$  is a functor
- $F(f \times g) = F f \times F g$

## Instance deduction

From corollary 2.1 we can deduce that:

$\mathcal{D}^+ (f \times g) = \lambda(a, b) \rightarrow \mathbf{let} \{ (c, f') = \mathcal{D}^+ f a; (d, g') = \mathcal{D}^+ g b \}$   
 $\mathbf{in} ((c, d), f' \times g')$

Deriving  $F$  from  $\hat{\mathcal{D}}$  leaves us with the following definition:

$\mathcal{D} (\mathcal{D}^+ f) \times \mathcal{D} (\mathcal{D}^+ g) = \mathcal{D} (\mathcal{D}^+ (f \times g))$

Using the same method as before, we replace  $\mathcal{D}^+$  with its definition and generalize the condition:

$\mathcal{D} f \times \mathcal{D} g =$

$\mathcal{D} (\lambda(a, b) \rightarrow \mathbf{let} \{ (c, f') = f a; (d, g') = g b \} \mathbf{in} ((c, d), f' \times g'))$

and this is enough for our new instance.

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# Instance deduction

## Categorical instance we've deduced

**instance** *Monoidal*  $\mathcal{D}$  **where**

$$\mathcal{D} f \times \mathcal{D} g = \mathcal{D} (\lambda(a, b) \rightarrow \mathbf{let} \{ (c, f') = f a; (d, g') = g b \} \\ \mathbf{in} ((c, d), f' \times g'))$$

## Cartesian categories and functors

**class** *Monoidal*  $k \Rightarrow$  *Cartesian*  $k$  **where**

$exl :: (a, b) ' k ' a$

$exr :: (a, b) ' k ' b$

$dup :: a ' k ' (a, a)$

**instance** *Cartesian*  $(\rightarrow)$  **where**

$exl = \lambda(a, b) \rightarrow a$

$exr = \lambda(a, b) \rightarrow b$

$dup = \lambda a \rightarrow (a, a)$

A cartesian functor  $F$  between categories  $\mathcal{U}$  and  $\mathcal{V}$  is such that:

- $F$  is a monoidal functor
- $F\ exl = exl$
- $F\ exp = exp$
- $F\ dup = dup$

# Instance deduction

From corollary 3.1 and from  $exl$ ,  $exr$  and  $dup$  being linear functions we can deduce that:

$$\mathcal{D}^+ exl = \lambda p \rightarrow (exl\ p, exl)$$

$$\mathcal{D}^+ exr = \lambda p \rightarrow (exr\ p, exr)$$

$$\mathcal{D}^+ dup = \lambda p \rightarrow (dup\ a, dup)$$

With this in mind we can arrive at our instance:

$$exl = \mathcal{D} (\mathcal{D}^+ exl)$$

$$exr = \mathcal{D} (\mathcal{D}^+ exr)$$

$$dup = \mathcal{D} (\mathcal{D}^+ dup)$$

## Instance deduction

Replacing  $\mathcal{D}^+$  with its definition and remembering linearD's definition we can obtain:

$exl = \text{linearD } exl$

$exr = \text{linearD } exr$

$dup = \text{linearD } dup$

and convert this directly into a new instance:

**Categorical instance we've deduced**

**instance** *Cartesian D* **where**

*$exl = \text{linearD } exl$*

*$exr = \text{linearD } exr$*

*$dup = \text{linearD } dup$*

# Cocartesian category

This type of categories is the dual of the cartesian type of categories.

## Note

In this article coproducts are categorical products, i.e., biproducts

## Definition

```
class Category  $k \Rightarrow \text{Cocartesian } k$  where
  inl ::  $a \text{ ' } k \text{ ' } (a, b)$ 
  inr ::  $b \text{ ' } k \text{ ' } (a, b)$ 
  jam ::  $(a, a) \text{ ' } k \text{ ' } a$ 
```

# Cocartesian functors

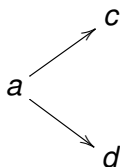
## Cocartesian functor definition

A cocartesian functor  $F$  between categories  $\mathcal{U}$  and  $\mathcal{V}$  is such that:

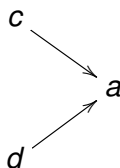
- $F$  is a functor
- $F \text{ inl} = \text{inl}$
- $F \text{ inr} = \text{inr}$
- $F \text{ jam} = \text{jam}$

# Fork and Join

- $\Delta :: \text{Cartesian } k \Rightarrow (a \text{ ' } k' \text{ } c) \rightarrow (a \text{ ' } k' \text{ } d) \rightarrow (a \text{ ' } k' \text{ } (c \times d))$



- $\nabla :: \text{Cartesian } k \Rightarrow (c \text{ ' } k' \text{ } a) \rightarrow (d \text{ ' } k' \text{ } a) \rightarrow ((c \times d) \text{ ' } k' \text{ } a)$





## Instance of $\rightarrow^+$

**newtype**  $a \rightarrow^+ b = \text{AddFun } (a \rightarrow b)$

**instance** *Category*  $(\rightarrow^+)$  **where**

**type** *Obj*  $(\rightarrow^+) = \text{Additive}$

*id* = *AddFun id*

*AddFun g*  $\circ$  *AddFun f* = *AddFun (g  $\circ$  f)*

**instance** *Monoidal*  $(\rightarrow^+)$  **where**

*AddFun f*  $\times$  *AddFun g* = *AddFun (f  $\times$  g)*

**instance** *Cartesian*  $(\rightarrow^+)$  **where**

*exl* = *AddFun exl*

*exr* = *AddFun exr*

*dup* = *AddFun dup*

# Instance of $\rightarrow^+$

**instance** *Cocartesian* ( $\rightarrow^+$ ) **where**

*inl* = *AddFun inlF*

*inr* = *AddFun inrF*

*jam* = *AddFun jamF*

*inlF* :: *Additive*  $b \Rightarrow a \rightarrow a \times b$

*inrF* :: *Additive*  $a \Rightarrow b \rightarrow a \times b$

*jamF* :: *Additive*  $a \Rightarrow a \times a \rightarrow a$

*inlF* =  $\lambda a \rightarrow (a, 0)$

*inrF* =  $\lambda b \rightarrow (0, b)$

*jamF* =  $\lambda(a, b) \rightarrow a + b$

# NumCat definition

**class** *NumCat* *k a* **where**

*negateC* :: *a* ' *k* ' *a*

*addC* :: (*a* × *a*) ' *k* ' *a*

*mulC* :: (*a* × *a*) ' *k* ' *a*

...

**instance** *Num* *a* ⇒ *NumCat* (→) *a* **where**

*negateC* = *negate*

*addC* = *uncurry* (+)

*mulC* = *uncurry* (\*)

...

$$\mathcal{D}(\text{negate } u) = \text{negate } (\mathcal{D} u)$$

$$\mathcal{D}(u + v) = \mathcal{D} u + \mathcal{D} v$$

$$\mathcal{D}(u * v) = u * \mathcal{D} v + v * \mathcal{D} u$$

- Imprecise on the nature of  $u$  and  $v$ .
- A precise and simpler definition would be to differentiate the operations themselves.

**class** *Scalable* *k a* **where**

*scale* ::  $a \rightarrow (a \text{ ' } k \text{ ' } a)$

**instance** *Num* *a*  $\Rightarrow$  *Scalable*  $(\rightarrow^+)$  *a* **where**

*scale* *a* = *AddFun*  $(\lambda da \rightarrow a * da)$

**instance** *NumCat* *D* **where**

*negateC* = *linearD* *negateC*

*addC* = *linearD* *addC*

*mulC* = *D*  $(\lambda(a, b) \rightarrow (a * b, \text{scale } b \nabla \text{scale } a))$

**instance** *FloatingCat* *D* **where**

*sinC* = *D*  $(\lambda a \rightarrow (\sin a, \text{scale } (\cos a)))$

*cosC* = *D*  $(\lambda a \rightarrow (\cos a, \text{scale } (-\sin a)))$

*expC* = *D*  $(\lambda a \rightarrow \text{let } e = \exp a \text{ in } (e, \text{scale } e))$

...

# Examples

$sqr :: Num\ a \Rightarrow a \rightarrow a$

$sqr\ a = a * a$

$magSqr :: Num\ a \Rightarrow a \times a \rightarrow a$

$magSqr\ (a, b) = sqr\ a + sqr\ b$

$cosSinProd :: Floating\ a \Rightarrow a \times a \rightarrow a \times a$

$cosSinProd\ (x, y) = (cos\ z, sin\ z) \textbf{ where } z = x * y$

With a compiler plugin we can obtain

$sqr = mulC \circ (id \Delta id)$

$magSqr = addC \circ (mulC \circ (exl \Delta exl) \Delta mulC \circ (exr \Delta exr))$

$cosSinProd = (cosC \Delta sinC) \circ mulC$

# Generalizing Automatic Differentiation

**newtype**  $D_k$   $a$   $b = D (a \rightarrow b \times (a ' k ' b))$

*linearD* ::  $(a \rightarrow b) \rightarrow (a ' k ' b) \rightarrow D_k a b$

*linearD*  $f$   $f' = D (\lambda a \rightarrow (f a, f'))$

**instance** *Category*  $k \Rightarrow$  *Category*  $D_k$  **where**

**type** *Obj*  $D_k =$  *Additive*  $\wedge$  *Obj*  $k$  ...

**instance** *Monoidal*  $k \Rightarrow$  *Monoidal*  $D_k$  **where** ...

**instance** *Cartesian*  $k \Rightarrow$  *Cartesian*  $D_k$  **where** ...

**instance** *Cocartesian*  $k \Rightarrow$  *Cocartesian*  $D_k$  **where**

*inl* = *linearD* *inlF* *inl*

*inr* = *linearD* *inrF* *inr*

*jam* = *linearD* *jamF* *jam*

**instance** *Scalable*  $k\ s \Rightarrow \text{NumCat } D_k\ s$  **where**  
*negateC* = *linearD negateC negateC*  
*addC* = *linearD addC addC*  
*mulC* = *D* ( $\lambda(a, b) \rightarrow (a * b, \text{scale } b \nabla \text{scale } a)$ )



# Matrices

There exists three, non-exclusive, possibilities for a nonempty matrix  $W$ :

- width  $W = \text{height } W = 1$ ;
- $W$  is the horizontal juxtaposition of two matrices  $U$  and  $V$ , where height  $W = \text{height } U = \text{height } V$  and width  $W = \text{width } U + \text{width } V$ ;
- $W$  is the vertical juxtaposition of two matrices  $U$  and  $V$ , where width  $W = \text{width } U = \text{width } V$  and height  $W = \text{height } U + \text{height } V$ .

## Extracting a Data Representation

In machine learning, a Gradient-based optimization works by searching for local minima in the domain of a differentiable function  $f :: a \rightarrow s$ . Each step in the search is in the direction opposite of the gradient of  $f$ , which is a vector form of  $\mathcal{D} f$ .

Given a linear map  $f' :: U \multimap V$  represented as a function, it is possible to extract a Jacobian matrix by applying  $f$  to every vector in a basis of  $U$ .

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# Generalized Matrices

Given a scalar field  $s$ , a free vector space has the form  $p \rightarrow s$  for some  $p$ , where the cardinality of  $p$  is the dimension of the vector space and there exists a finite number of values for  $p$ .

In particular, we can represent vector spaces over a given field as a representable functor, i.e., a functor  $F$  such that:

$$\exists p \forall s \ F \ s \cong \ p \rightarrow s$$

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## A short introduction

- We've derived and generalized an AD algorithm using categories.
- With fully right-associated compositions this algorithm becomes a forward-mode AD and with fully left-associated becomes a reverse-mode AD.
- We want to obtain generalized FAD and RAD algorithms.
- How do we describe this in Categorical notation?

# Converting morfisms

Given a category  $k$  we can represent its morfisms the following way:

## Left-Compose functions

$f :: a' \rightarrow k' \rightarrow b \Rightarrow (\circ f) :: (b' \rightarrow k' \rightarrow r) \rightarrow (a' \rightarrow k' \rightarrow r)$  where  $r$  is any object of  $k$ .

If  $h$  is the morfism we'll compose with  $f$  then  $h$  is the continuation of  $f$ .

# Instance deduction

## Defining new type

**newtype**  $\text{Cont}_k^f a b = \text{Cont} ((b \text{ ' } k' \text{ } r) \rightarrow (a \text{ ' } k' \text{ } r))$

## Functor derived from type

$\text{cont} :: \text{Category } k \Rightarrow (a \text{ ' } k' \text{ } b) \rightarrow \text{Cont}_k^f a b$   
 $\text{cont } f = \text{Cont } (\circ f)$



## Instance deduction

**instance** *Category*  $k \Rightarrow \text{Category } \text{Cont}_k^r$  **where**

*id* = *Cont id*

*Cont g*  $\circ$  *Cont f* = *Cont (f*  $\circ$  *g)*

**instance** *Monoidal*  $k \Rightarrow \text{Monoidal } \text{Cont}_k^r$  **where**

*Conf f*  $\times$  *Cont g* = *Cont (join*  $\circ$  (*f*  $\times$  *g)*  $\circ$  *unjoin)*

**instance** *Cartesian*  $k \Rightarrow \text{Cartesian } \text{Cont}_k^r$  **where**

*exl* = *Cont (join*  $\circ$  *inl)*; *exr* = *Cont (join*  $\circ$  *inr)*

*dup* = *Cont (jam*  $\circ$  *unjoin)*

**instance** *Cocartesian*  $k \Rightarrow \text{Cocartesian } \text{Cont}_k^r$  **where**

*inl* = *Cont (exl*  $\circ$  *unjoin)*; *inr* = *Cont (exr*  $\circ$  *unjoin)*

*jam* = *Cont (join*  $\circ$  *dup)*

**instance** *Scalable*  $k$  *a*  $\Rightarrow \text{Scalable } \text{Cont}_k^r$  *a* **where**

*scale s* = *Cont (scale s)*

## A short introduction

Due to its widespread use in ML we'll talk about a specific case of RAD: computing gradients (derivatives of functions with scalar codomains).

A vector space  $A$  over a scalar field  $s$  has  $A \multimap s$  as its dual. Each linear map in  $A \multimap s$  can be represented in the form of  $\text{dot } u$  for some  $u :: A$  where

### Definition and instanciation

**class** *HasDot* ( $S$ )  $u$  **where**  $\text{dot} :: u \rightarrow (u \multimap s)$

**instance** *HasDot* ( $IR$ )  $IR$  **where**  $\text{dot} = \text{scale}$

**instance** (*HasDot* ( $S$ )  $a$ , *HasDot* ( $S$ )  $b$ )

$\Rightarrow$  *HasDot* ( $S$ ) ( $a \times b$ )

**where**  $\text{dot } (u, v) = \text{dot } u \Delta \text{dot } v$

# Instance deduction

The internal representation of  $Cont^s_{\circ} a b$  is  $(b \multimap s) \rightarrow (a \multimap s)$  which is isomorphic to  $(a \rightarrow b)$ .

Type definition for duality

**newtype**  $Dual_k a b = Dual (b ' k' a)$

## Instance deduction

All we need to do to create dual representations of linear maps is to convert from  $Cont_k^S$  to  $Dual_k$  using a functor:

### Functor definition

$$\begin{aligned} asDual &:: (HasDot\ (S)\ a, HasDot\ (S)\ b) \Rightarrow \\ &\quad ((b \multimap s) \rightarrow (a \multimap s)) \rightarrow (b \multimap a) \\ asDual\ (Cont\ f) &= Dual\ (onDot\ f) \end{aligned}$$

where

$$\begin{aligned} onDot &:: (HasDot\ (S)\ a, HasDot\ (S)\ b) \Rightarrow \\ &\quad ((b \multimap s) \rightarrow (a \multimap s)) \rightarrow (b \multimap a) \\ onDot\ f &= dot^{-1} \circ f \circ dot \end{aligned}$$

## Instance deduction

**instance** *Category*  $k \Rightarrow \text{Category } \text{Dual}_k$  **where**

*id* = *Dual id*

*Dual g*  $\circ$  *Dual f* = *Dual (f*  $\circ$  *g)*

**instance** *Monoidal*  $k \Rightarrow \text{Monoidal } \text{Dual}_k$  **where**

*Dual f*  $\times$  *Dual g* = *Dual (f*  $\times$  *g)*

**instance** *Cartesian*  $k \Rightarrow \text{Cartesian } \text{Dual}_k$  **where**

*exl* = *Dual inl*; *exr* = *Dual inr*

*dup* = *Dual jam*

**instance** *Cocartesian*  $k \Rightarrow \text{Cocartesian } \text{Dual}_k$  **where**

*inl* = *Dual exl*; *inr* = *Dual exr*

*jam* = *Dual dup*

**instance** *Scalable*  $k \Rightarrow \text{Scalable } \text{Dual}_k$  **where**

*scale s* = *Dual (scale s)*

# Final notes

- $(\nabla)$  and  $(\Delta)$  mutually dualize  
 $(Dual\ f\ \nabla\ Dual\ g) = Dual\ (f\ \Delta\ g)$  and  $Dual\ f\ \Delta\ Dual\ g = Dual\ (f\ \nabla\ g)$
- Using the definition from chapter 8 we can determine that the duality of a matrix corresponds to its transposition

## Fowards-mode Automatic Differentiation(FAD)

We can use the same deductions we've done in Cont and Dual to derive a category with full right-side association, thus creating a generized FAD algorithm.

This algorithm is far more appropriate for low dimension domains.

### Type definition and functor from type

**newtype**  $Begin_k^r a b = Begin ((r ' k' a) \rightarrow (r ' k' b))$

$begin :: Category\ k \Rightarrow (a ' k' b) \rightarrow Begin_k^r a b$

$begin\ f = Begin\ (f \circ)$

We can derive categorical instances from the functor above and we can choose  $r$  to be the scalar field  $s$ , noting that  $s \multimap a$  is isomorphic to  $a$ .

# Scaling Up

- Practical applications often involve high-dimensional spaces.
- Binary products are a very inefficient and unwieldy way of encoding high-dimensional spaces.
- A practical alternative is to consider n-ary products as representable functors.

**class** *Category*  $k \Rightarrow \text{Monoidall } k \ h$  **where**

*crossl* ::  $h \ (a' \ k' \ b) \rightarrow (h \ a' \ k' \ h \ b)$

**instance** *Zip*  $h \Rightarrow \text{Monoidall } (\rightarrow) \ h$  **where**

*crossl* = *zipWith id*



**class** *Monoidall*  $k\ h \Rightarrow \text{CartesianI } k\ h$  **where**

*exl*  $:: h\ (h\ a\ 'k\ 'a)$

*repl*  $:: a\ 'k\ 'h\ a$

**instance** (*Representable*  $h$ , *Zip*  $h$ , *Pointed*  $h$ )  $\Rightarrow$

*CartesianI*  $(\rightarrow)\ h$  **where**

*exl* = *tabulate* (*flip index*)

*repl* = *point*

- The following is not the class the author was thinking

**class** *Representable*  $h$  **where**

**type** *Rep*  $h :: *$

*tabulate*  $:: (\text{Rep } h \rightarrow a) \rightarrow h\ a$

*index*  $:: h\ a \rightarrow \text{Rep } h \rightarrow a$

**class** *Monoidall* *k h*  $\Rightarrow$  *Cocartesianl* *k h* **where**

*inl* :: *h* (*a* ' *k* ' *h a*)

*jaml* :: *h a* ' *k* ' *a*

**instance** (*Monoidall* *k h*, *Zip h*)  $\Rightarrow$  *Monoidall* *D<sub>k</sub> h* **where**

*crossl* *fs* = *D* ((*id*  $\times$  *crossl*)  $\circ$  *unzip*  $\circ$  *crossl* (*fmap unD fs*))

**instance** (*Cocartesianl* ( $\rightarrow$ ) *h*, *Cartesianl* *k h*, *Zip h*)  $\Rightarrow$

*Cartesianl* *D<sub>k</sub> h* **where**

*exl* = *linearD* *exl* *exl*

*repll* = *zipWith linearD repll repll*

**instance** (*Cocartesianl* *k h*, *Zip h*)  $\Rightarrow$  *Cocartesianl* *D<sub>k</sub> h* **where**

*inl* = *zipWith linearD inlF inl*

*jaml* = *linearD sum jaml*

**class** *Monoidall* *k h*  $\Rightarrow$  *Cocartesianl* *k h* **where**

*inl* :: *h* (*a* ' *k* ' *h a*)

*jaml* :: *h a* ' *k* ' *a*

**instance** (*Monoidall* *k h*, *Zip h*)  $\Rightarrow$  *Monoidall* *D<sub>k</sub> h* **where**

*crossl* *fs* = *D* ((*id*  $\times$  *crossl*)  $\circ$  *unzip*  $\circ$  *crossl* (*fmap unD fs*))

**instance** (*Cocartesianl* ( $\rightarrow$ ) *h*, *Cartesianl* *k h*, *Zip h*)  $\Rightarrow$

*Cartesianl* *D<sub>k</sub> h* **where**

*exl* = *zipWith linearD exl exl*

*repll* = *linearD repll repll*

**instance** (*Cocartesianl* *k h*, *Zip h*)  $\Rightarrow$  *Cocartesianl* *D<sub>k</sub> h* **where**

*inl* = *zipWith linearD inlF inl*

*jaml* = *linearD sum jaml*

# Conclusion

- Suggests that some of the work referred to does just a part of this article.
- This article ([Elliott 2018][2]) is a follow up of [Elliott 2017][1]
- Suggests that this implementation is simple, efficient, it can free memory dinamically (RAD) and is naturally parallel.
- Future work are detailed performace analysis; higher-order differentiation and automatic incrementation (continuing previous work [Elliott 2017][1])



ELLIOTT, C.

Compiling to categories.

*Proc. ACM Program. Lang.* 1, ICFP (Aug. 2017),  
27:1–27:27.



ELLIOTT, C.

The simple essence of automatic differentiation.

*Proc. ACM Program. Lang.* 2, ICFP (July 2018),  
70:1–70:29.