# Bundles, Lenses \& Machine Learning 

Jules Hedges ${ }^{1}$<br>joint work with<br>Brendan Fong ${ }^{2}$ Eliana Lorch ${ }^{3}$ David Spivak ${ }^{2}$<br>${ }^{1}$ Max Planck Institute for Mathematics in the Sciences<br>${ }^{2} \mathrm{MIT}$<br>${ }^{3}$ University of Oxford<br>SYCO 5, Birmingham

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## Motivation

Machine learning is categorical in 2 different ways:

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```
                    Backprop As Functor
(compositional description of ML with monoidal categories)
                                    +
ML as differential geometry
```

In this talk: smoosh them together
(why? Why not)

Machine learning is categorical in 2 different ways:

In this talk: smoosh them together
(why? Why not)

It clarifies Backprop as Functor more than anything else

Bundles, Lenses \& Machine Learning

Definition (Fong, Spivak \& Tuyéras) : An open learner $X \rightarrow Y$ consists of:

- A set $P$ of parameters


## Open learners

Bundles,

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Composition of open learners is fiddly

They form a symmetric monoidal category called Learn

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A lens $X \rightarrow Y$ is a function $X \rightarrow Y$ and a function $X \times Y \rightarrow X$

Composition of lenses is also fiddly!

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## Lenses

A lens $X \rightarrow Y$ is a function $X \rightarrow Y$ and a function $X \times Y \rightarrow X$

Composition of lenses is also fiddly!

Theorem (Fong \& Johnson): Open learners compose by pullback of lenses:


Define a category ${ }^{1}$ Para $(\mathcal{C})$ by:
${ }^{1}$ who cares about monoidal bicategories

## The Para construction

Let $\mathcal{C}$ be a monoidal category
Define a category ${ }^{1}$ Para $(\mathcal{C})$ by:

- Objects: objects of $\mathcal{C}$
- Morphisms $X \rightarrow Y$ : pair $(A, f), A$ object of $\mathcal{C}$, $f: X \otimes A \rightarrow Y$
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- Composition of $(B, g) \circ(A, f)$ :

$$
(A \otimes B, X \otimes A \otimes B \xrightarrow{f \otimes B} Y \otimes B \xrightarrow{g} Z)
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$\otimes$ lifts to a monoidal product on Para $(\mathcal{C})$
${ }^{1}$ who cares about monoidal bicategories

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## The structure of Para(-)

A lax symmetric monoidal functor $F: \mathcal{C} \rightarrow \mathcal{D}$ lifts to

$$
\operatorname{Para}(F): \operatorname{Para}(\mathcal{D}) \rightarrow \operatorname{Para}(\mathcal{D})
$$

by

$$
F(A, f): F(X) \otimes F(A) \xrightarrow{\varphi} F(X \otimes A) \xrightarrow{F(f)} F(Y)
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Proposition (probably): Para(-) defines a monad on [symmetric monoidal categories, lax symmetric monoidal functors]

Theorem (Fong, Spivak \& Tuyéras): Fix a learning rate $\varepsilon>0$ and a differentiable cost function ${ }^{2} C: \mathbb{R}^{2} \rightarrow \mathbb{R}$.

[^0]
## Backprop as Functor

Theorem (Fong, Spivak \& Tuyéras): Fix a learning rate $\varepsilon>0$ and a differentiable cost function ${ }^{2} C: \mathbb{R}^{2} \rightarrow \mathbb{R}$.

Then there is a symmetric monoidal functor $F_{\varepsilon, C}: \operatorname{Para}(E \mathbf{u c}) \rightarrow$ Learn defined by

- On objects $X \mapsto$ underlying set of $X$
${ }^{2}$ such that every $\frac{\partial}{\partial y} C(x, y)$ is invertible


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- Parameters $P$
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- Parameters $P$
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- Update $U(a, x, y)=a-\varepsilon \nabla_{a} E(a, x, y)$
- Request $r(a, x, y)=($ too awkward to write down)
where $E(a, x, y)=\sum_{i=1}^{\operatorname{dim}(Y)} C\left(f(p, x)_{i}, y_{i}\right)$ is total error
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where $E(a, x, y)=\sum_{i=1}^{\operatorname{dim}(Y)} C\left(f(p, x)_{i}, y_{i}\right)$ is total error
Update is gradient descent, and request is backpropagation
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## ML doesn't work like that

Actual backpropagation backpropagates gradients

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This is a hack because objects of Learn doesn't have differentiable structure
(The benefit is Learn is more general than just ML)

Work in a category with finite limits
A bundle over $X$ is a morphism $\underset{\underset{X}{ }}{\stackrel{\rightharpoonup}{p}}$

## Bundles

$E$

## Bundles

Work in a category with finite limits

Examples:


## Bundles

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TM
(2) Tangent bundle over a differentiable manifold

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Examples:


TM
(2) Tangent bundle over a differentiable manifold
$T^{*} \mathcal{M}$
(3) Cotangent bundle

$$
\begin{gathered}
\downarrow \pi^{*} \\
\mathcal{M}
\end{gathered}
$$

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Motivation
Backprop as Functor

## Bundles over Euclidean spaces

If $X=\mathbb{R}^{n}$ is a Euclidean space then

- every $T_{x}(X) \cong X$

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Bundles,

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Moreover:

- every $T_{X}^{*}(X) \cong X$ unnaturally (since $X^{*} \cong X$ )

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Nb. Euc doesn't have finite limits, so we work in Top

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Motivation
Backprop as Functor

Bundles
Putting it together

## Morphisms of bundles

## $E \quad F$ <br> A bundle morphism $f: \downarrow p \rightarrow \downarrow q$ is: <br> $X \quad Y$

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## Morphisms of bundles



- Morphisms $f: X \rightarrow Y$ and $f^{\#}: X \times_{Y} F \rightarrow E$

Bundles,
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- Morphisms $f: X \rightarrow Y$ and $f^{\#}: X \times_{Y} F \rightarrow E$
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- Equivalently: $f$ such that $X \times_{Y} F \rightarrow X$ factors through $p$


## Morphisms of bundles



- Morphisms $f: X \rightarrow Y$ and $f^{\#}: X \times_{Y} F \rightarrow E$
- such that

$$
\begin{aligned}
& X \times_{y} F \longrightarrow F
\end{aligned}
$$

is a pullback

- Equivalently: $f$ such that $X \times_{Y} F \rightarrow X$ factors through $p$
"Every algebraic geometer knows this definition" - David Spivak

Bundles, Lenses \& Machine Learning

## Motivation

Backprop as Functor

Bundles
Putting it together

## The category of bundles



Identity morphism:

## The category of bundles



Composition of morphisms:


## Where does this come from?

From the Grothendieck construction:

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$$

This buys us (conjecture) a monoidal structure:

$$
\begin{array}{ccc}
E & F & E \times F \\
\underset{\downarrow}{p} \otimes \underset{ }{\downarrow}= & \underset{\sim}{q}= \\
X & Y & X \times Y
\end{array}
$$

(this might not be the right one!)

A (bimorphic) lens $\lambda:(S, T) \rightarrow(A, B)$ consists of:

- a morphism $\lambda_{v}: S \rightarrow A$ called view
- a morphism $\lambda_{u}: S \times B \rightarrow T$ called update


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Theorem (Lambek): $\operatorname{coKl}(X \times-) \cong \mathcal{C}[x]$, where $\mathcal{C}[x]$ is the polynomial category formed by freely adjoining $x: 1 \rightarrow X$ and closing under finite products

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Motivation
Backprop as Functor Bundles

Putting it together

## Lenses are bundle morphisms

## Another theorem (Lambek): $\operatorname{coEM}(X \times-) \cong \mathcal{C} / X$

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Grothendieck them all together: $\operatorname{Lens}(\mathcal{C}) \rightarrow \operatorname{Bund}(\mathcal{C})$ It takes a lens $\lambda:(S, T) \rightarrow(A, B)$ to the bundle morphism


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## Morphisms of contangent bundles

There is a functor $\operatorname{Cot}(-):$ DiffMfd $\rightarrow$ Bund(Top)

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It takes $f: X \rightarrow Y$ to

$$
\begin{array}{ccc}
X \times{ }_{Y} T^{*}(Y) & \longrightarrow T^{*}(Y) \\
f^{\prime} \downarrow & & \\
T^{*}(X) & & \pi^{*} \mid \\
\pi^{*} \downarrow & & \downarrow \\
X & f & Y
\end{array}
$$

where $f^{\prime}:(x, c) \mapsto\left(x, c \circ J_{x}(f)\right)$

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where $f^{\prime}:(x, c) \mapsto\left(x, c \circ J_{x}(f)\right)$
$J_{x}(f)$ is the Jacobian (matrix of partial derivatives) of $f$ at $x$

Functorality of $\boldsymbol{\operatorname { C o t }}(-)$ :

$$
\begin{aligned}
& X \times_{Z} T^{*}(Z) \longrightarrow Y \times_{Z} T^{*}(Z) \longrightarrow T^{*}(Z) \\
& \begin{array}{cc}
f^{*}\left(g^{\prime}\right) \downarrow \\
X \times_{Y} T^{*}(Y) \longrightarrow & g^{\prime} \downarrow \\
& T^{*}(Y)
\end{array} \\
& \begin{array}{c}
f^{\prime} \downarrow \\
T^{*}(X)
\end{array} \\
& \pi^{*} \downarrow \\
& \pi^{*} \downarrow \\
& \underset{X}{f} Y \xrightarrow{\downarrow} \stackrel{\downarrow}{Z}
\end{aligned}
$$

## The chain rule

Functorality of $\operatorname{Cot}(-)$ :

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& \pi^{*} \downarrow \\
& X \longrightarrow \quad Y \xrightarrow{f} Z
\end{aligned}
$$

$(g \circ f)^{\prime}=f^{\prime} \circ f^{*}\left(g^{\prime}\right)$ is the chain rule in differential geometry

## From Para(Bund(Top)) to Learn

Consider a morphism of Para(Bund(Top)) in the image of

$$
\text { Para(Cot) }: \operatorname{Para}(\text { Euc }) \rightarrow \operatorname{Para}(\text { Bund(Top) })
$$

It looks like

$$
\begin{aligned}
& (X \times A) \times_{Y} T^{*}(Y) \longrightarrow Y
\end{aligned}
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## From Para(Bund(Top)) to Learn

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We're going to turn it into an open learner, given $\varepsilon>0$ and differentiable $C: \mathbb{R}^{2} \rightarrow \mathbb{R}$

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## The setup

Obviously, parameters are $A$ and implementation is $f$

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We need to define $\langle U, r\rangle: A \times X \times Y \rightarrow A \times X$
so, fix $a \in A, x \in X$ and $y \in Y$
and fix the total error $C_{y}\left(y^{\prime}\right)=\sum_{i=1}^{\operatorname{dim}(Y)} C\left(y_{i}, y_{i}^{\prime}\right)$

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Consider the diagram...

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## The brain exploding part



## The part we don't understand

Now: Chase $1 \in \mathbb{R}$ to $T^{*}(X \times A)$ and then apply

$$
\mu_{\varepsilon}: T^{*}(X \times A) \rightarrow X \times A
$$

The result is $\langle r, U\rangle(a, x, y)$

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$\mu_{\varepsilon}$ takes a finite step in the gradient direction:

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\mu_{\varepsilon}((x, a),(v, w))=(x+v, a+\varepsilon w)
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What is $\mu_{\varepsilon}$ ? We couldn't find any nice properties
It looks a bit like a thing called an exponential map

## The catch

Conjecture: This defines a symmetric monoidal functor

$$
\operatorname{Para}(\text { Bund }(\text { Top })) \supseteq \operatorname{Im}(\text { Para }(\text { Cot })) \rightarrow \text { Learn }
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The catch: We think Para(Cot) is an equivalence of categories onto its image

So, we've just rewritten Backprop as Functor in a different way!

## Even more hard questions

What happens if we extend the functor to the whole of Para(Bund(Top))? We have no idea!

Optimistic hope: This allows defining general "ML-like" systems, not necessarily involving gradients (eg. "discrete ML" on Bayesian networks)


[^0]:    ${ }^{2}$ such that every $\frac{\partial}{\partial y} C(x, y)$ is invertible

