

# GT Deep Learning: 04

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Introduction

Evaluation

Finite Difference

Symbolic Differentiation

Automatic Differentiation

## Setup

Neural Network  $\mathbf{x} \mapsto F(\mathbf{x}, p_1, \dots, p_d)$

Supervised Learning Data  $(\mathbf{x}_i, s_i)_{1 \leq i \leq N}$

Maximum Likelihood Minimize  $J(p_1, \dots, p_d)$

Gradient Descent Compute  $\nabla J(p_1, \dots, p_d)$

Introduction

**Evaluation**

Finite Difference

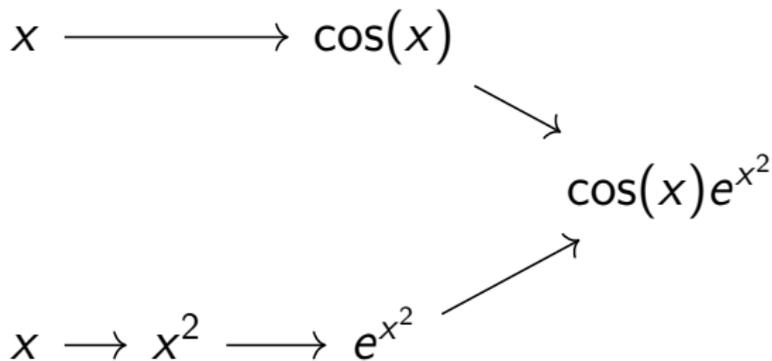
Symbolic Differentiation

Automatic Differentiation

## Evaluation

- ▶ Evaluating an Expression (Meaning?)
- ▶ Parser: Expression  $\mapsto$  Evaluation Tree
- ▶  One Expression, Multiple Trees!
- ▶ Tree  $\implies$  Recursive Structure
- ▶ Example:  $u(x) = \cos(x)e^{x^2}$

## Evaluation Tree



**Evaluation:** Left to Right with numbers!

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## Finite Difference

Formula  $u'(x) \approx \frac{u(x+h)-u(x)}{h}$

Problem 1 Choice of  $h$ ?

Problem 2  Numerical Stability?

Problem 3 2 evaluation of  $u$

Problem 3'   $d$  variables  $\implies d + 1$  evaluations!

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## Symbolic Differentiation

**Goal**  $D : \text{E.T.}(u) \mapsto \text{E.T.}(u')$

**Reminder** E.T. of  $u(x) = \cos(x)e^{x^2}$ :

$x \longrightarrow \cos(\cdot)$

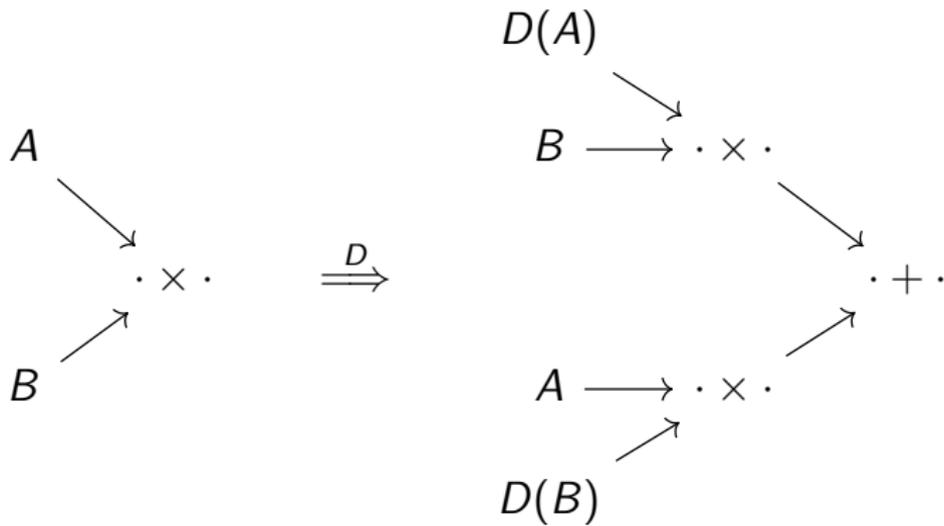
$\searrow$   
 $\cdot \times \cdot$

$x \longrightarrow (\cdot)^2 \longrightarrow \exp(\cdot)$

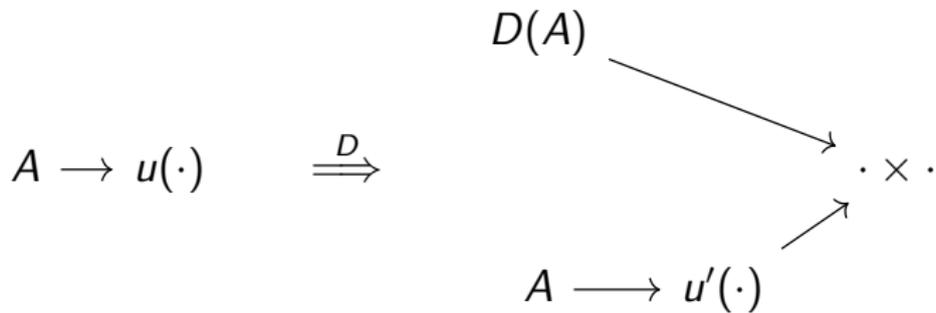
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# Multiplication Node

- ▶ Encodes  $(uv)' = u'v + uv'$
- ▶  $A$  and  $B$  subtrees



## Composition Node



## Summary

- ▶ From E.T.( $u$ ) Compute E.T.( $u'$ )!
- ▶ Problem 1: One tree for each  $(\partial_{p_k})_{1 \leq k \leq d}$
- ▶ Problem 2: Combinatorial Explosion

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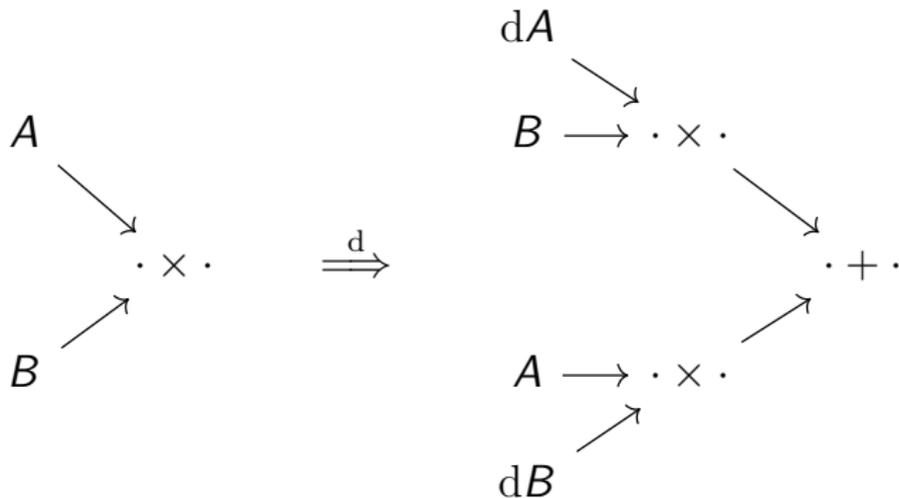
Automatic Differentiation

## Partial Derivative < Differential

- ▶  $F : \mathbb{R}^d \rightarrow \mathbb{R}$
- ▶  $\nabla F(\mathbf{p}) = (\partial_{p_1} F(\mathbf{p}), \dots, \partial_{p_d} F(\mathbf{p}))$
- ▶ But also  $dF(\mathbf{p}) = \sum_{k=1}^d \partial_{p_k} F(\mathbf{p}) dp_k$
- ▶ Compute  $dF$  E.T.

## Multiplication Node II

- ▶ Encodes  $d(uv) = vdu + udv$
- ▶  $A$  and  $B$  subtrees



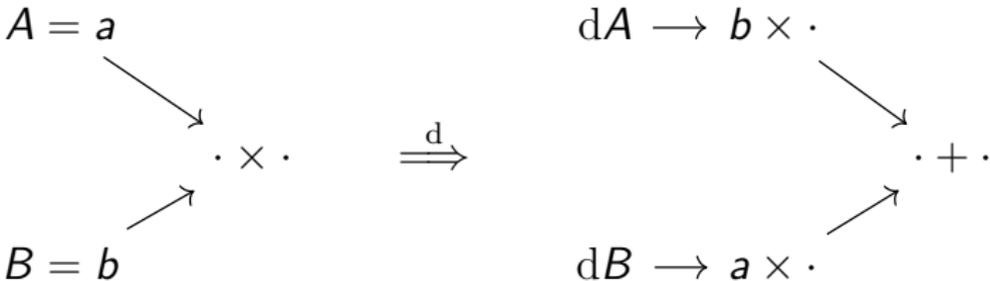
# Main Idea of Automatic Differentiation

**Forward Pass** All nodes of E.T. have specific values

**Backward Pass** S.D. + Specific Values

**Example** Multiplication Node

**Note**  $AB$ : subtrees,  $a b$ : numbers



## Example

- ▶ 1/2/1 Neural Network
- ▶ Explicit Formula
- ▶   $\neq$  Parser
- ▶ Blackboard: Forward then Backward
- ▶ Demonstration using Pytorch