Machine Learning for Symbolic Integration Algorithm Selection

Maple Conference– October 26, 2023

RASHID BARKET, MATTHEW ENGLAND, JÜRGEN GERHARD

COVENTRY UNIVERSITY & MAPLESOFT

BARKETR@COVENTRY.AC.UK





Motivation - Maple and Machine Learning

•Computer Algebra refers to the study and development of algorithms and software for manipulating mathematical expressions and other mathematical objects

•As a Computer Algebra System, Maple should always return the correct answer

• Alternatively, Maple shouldn't output anything at all if there is no answer or it cannot compute one!

• Machine Learning has seen many applications in various fields. Computer Algebra is now starting to catch up.

- A problem exists between Computer Algebra and Machine Learning
 - E.g. I build a model that has 99% accuracy for computing an integral given an expression. Is this acceptable?



Machine Learning and Integration

•Two approaches:

Directly solving a problem

- Compute the result of a task given an input
- E.g. Given an expression, calculate its integral
- Performance based on accuracy

$$x \sin(x) \longrightarrow \bigcirc -x \cos(x) + \sin(x)$$

Algorithm Selection

- If an algorithm can make an arbitrary choice, use ML to help guide that choice
- E.g. Given an expression, which integration rule should we first try
- Performance based on speed & output quality





Objective

• There are two objective functions we can consider when assessing how well a sub-algorithm does

- Output length
- Runtime



• Sub-algorithms selected are the ones that outputs the shortest expression.

• Could be that a sub-algorithm was successful but gave a longer answer so we consider that a fail



• Sub-algorithms are not mutually exclusive

Generating Data – Random Expressions

Deep Learning for Symbolic Mathematics - Lample G, Charton F (Meta AI research)

Mathematical expressions can be represented as trees:

- operators and functions as internal nodes
- numbers, constants and variables as leaves



Generating Data – (Integrand, Integral) pairs

Deep Learning for Symbolic Mathematics - Lample G, Charton F (Meta AI research)

- FWD: Integrate an expression f through a CAS to get F and add the pair (f, F) to the dataset.
- BWD: Differentiate an expression f to get f' and add the pair (f', f) to the dataset.
- IBP: Given two expressions f and g, calculate f' and g'. If $\int f'g$ is known then the following holds (integration-by-parts):

$$\int fg' = fg - \int f'g.$$

Thus we add the pair $(fg', fg - \int f'g)$ to the dataset.



The Dataset

• FWD

• BWD - Lample & Charton (2020) • IBP

- Risch Method Barket et al. (2023)
- The Substitution Rule $\int f(g(x))g'(x) \, dx$



LSTMs

- LSTM = Long Short-Term Memory
- A Neural Network architecture for handling sequence data (text, time series, etc.)
- Able to remember information far in the past (Long term memory) as well as use the information near the current step (short term memory)
- Performs much better than vanilla neural networks for tasks such as text classification, language translation, and time series predictions



$Accuracy = \frac{True \ Positives + True \ Negatives}{Total}$

 $Precision = \frac{True Positives}{True Positives + False Positives}$



Initial Results

Comparison against Maple

- We trained our ML model on FWD, IBP, Risch, and Sub data to predict the sub-algorithm with the smallest output
- The model is tested with 25,000 integrable expressions

	Maple	LSTM	Tie
Same Data Generation Methods	2,147	8,746	14,107
BWD	2,437	1,482	21,081

• Suggests bias in the dataset





int(f, x, method=risch)

 $x + \sin(\cos(x)) x$



Thank you! Questions?

