Automatic Retuning of Floating-Point Precision

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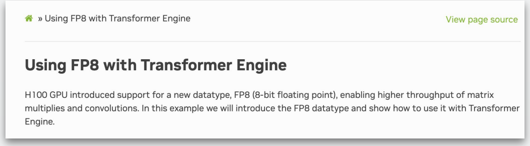
Choosing the right floating point precision is important

Too high a precision ⇨ For nothing - if we didn't need the precision

- More power
- Longer runtime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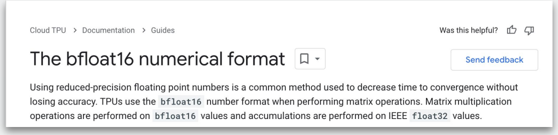
Using FP8 with Transformer Engine

H100 GPU introduced support for a new datatype, FP8 (8-bit floating point), enabling higher throughput of matrix multiplies and convolutions. In this example we will introduce the FP8 datatype and show how to use it with Transformer Engine.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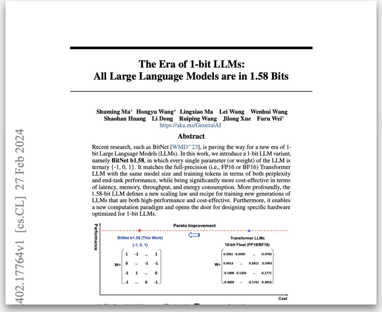
The bfloat16 numerical format   Send feedback

Using reduced-precision floating point numbers is a common method used to decrease time to convergence without losing accuracy. TPUs use the `bfloat16` number format when performing matrix operations. Matrix multiplication operations are performed on `bfloat16` values and accumulations are performed on IEEE `float32` values.


arXiv:2402.17764v1 [cs.CL] 27 Feb 2024

The Era of 1-bit LLMs: All Large Language Models are in 1.58 Bits

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https://aka.ms/GeneralAI

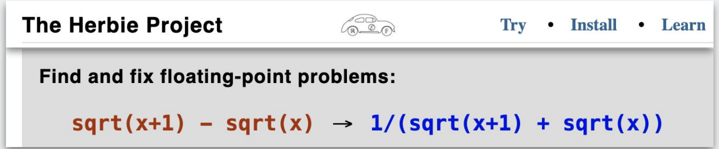
Abstract

Recent research, such as BitNet [WMD+23], is paving the way for a new era of 1-bit Large Language Models (LLMs). In this work, we introduce a 1-bit LLM variant, namely **BitNet b1.58**, in which every single parameter (or weight) of the LLM is ternary {-1, 0, 1}. It matches the full-precision (i.e., FP16 or BF16) Transformer LLM with the same model size and training tokens in terms of both perplexity and end-task performance, while being significantly more cost-effective in terms of latency, memory, throughput, and energy consumption. More profoundly, the 1.58-bit LLM defines a new scaling law and recipe for training new generations of LLMs that are both high-performance and cost-effective. Furthermore, it enables a new computation paradigm and opens the door for designing specific hardware optimized for 1-bit LLMs.

Too low?

- Useless results

  - some scientific applications require > 128 bit fp numbers to work


The Herbie Project   Try • Install • Learn

Find and fix floating-point problems:

`sqrt(x+1) - sqrt(x)  →  1/(sqrt(x+1) + sqrt(x))`

Future hardware...?

Existing Approaches to Re-tuning or exploration

Macros (#define float float8)

+ Easy to set up
- Programs will often fail to build (wrong size memory to copy, cannot cast to new type, conflicting names)
- Applies to entire program, not just the sub-computation we care about

Templating functions

- Requires rewriting code to be generic (and breaks library calls)
+ Easier compiler-level errors, and more brute force debugging than endless conflicts
+ Fast
- No analysis

Adapt

+ Analysis of errors
- Requires rewriting code
- Slow
- Does not reflect fp optimized state

Valgrind?

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- **Does not reflect fp optimized state**

Valgrind?

FP Optimizations

```
define fun():
  ...
  %c = fadd %a, %b : f32
  %e = fmul %d, %c : f32
  ...
```

```
define fun():
  ...
  %e = fma %a, %b, %d : f32
  ...
```

```
define fun():
  ...
  %c = call __fp_add(%a, %b) : %struct.fp
  %e = call __fp_mul(%d, %c) : %struct.fp
  ...
```

```
define fun():
  ...
  %c = call __fp_add(%a, %b) : %struct.fp
  %e = call __fp_mul(%d, %c) : %struct.fp
  ...
```

llvm: What is going on here???? I have no idea.

But what about optimization?

- Optimizations can change result! Sometimes good, sometimes bad
  - Program can now run faster at expense of error (e.g. fastmath)
  - Optimizers (e.g. Herbie) can optimize for more accurate!

⇩

- Source-level tooling can fail to predict actual results.
- Even better tools would be able to jointly optimize the precision and the computation!

`-fassociative-math`

> *Allow re-association of operands in series of floating-point operations.*

This allows the compiler to change the order of evaluation in a sequence of floating point operations. For example if you have an expression `(a + b) + c`, it can evaluate it instead as `a + (b + c)`. While these are mathematically equivalent with real numbers, they aren't equivalent in floating point arithmetic: the errors they incur can be different, in some cases quite significantly so:

```
julia> a = 1e9+1; b = -1e9; c = 0.1;

julia> (a+b)+c
1.1

julia> a+(b+c)
1.100000023841858
```

From Simon Byrne (https://simonbyrne.github.io/notes/fastmath/)

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Find and fix floating-point problems:

`sqrt(x+1) - sqrt(x)` → `1/(sqrt(x+1) + sqrt(x))`

Impact of optimizations?

On FPBench: **745 functions** with fp computation

```
clang -O3 -ffast-math ...
```

vs

```
clang -O0
```

Mismatched results on **124** of them

Impact of optimizations?

Mismatched results on **124**/745 functions

You may get unexpected results on real hardware

Our Approach

- We build off the Enzyme infrastructure for generating shadow computations from generic LLVM code (historically derivatives) to now generate new functions which replace floating representations.
- Apply optimization prior (and optionally after) floating tuning!
- No program rewriting required, just call the corresponding intrinsic function. (Or specify full-module effect on command line)

```
double
float    half    mpfr(5,20)    mpfr(5,20)    .....
```

Example Usage

```c
#define FROM 64
#define TO_E 5     // Exponent
#define TO_M 21    // Mantissa

double f(double x, double y) {
    return ...;
}

double a = 3, b = 4;

// Step 1: Call wrapper to convert inputs into specified precision
//         Here we convert from fp64 to fp32, using the old type
//         as storage for the truncated data.
a = __enzyme_truncate_mem_value(a, FROM, TO_E, TO_M);
b = __enzyme_truncate_mem_value(b, FROM, TO_E, TO_M);

// Step 2: Generate an fp32 version of the fp64 function
//         with our new intrinsic.
double res = __enzyme_truncate_mem_func(f, FROM, TO_E, TO_M)(a, b);

// Step 3: Convert the truncated result back into the full fp64.
res = __enzyme_expand_mem_value(res, FROM, TO_E, TO_M);
```

Example Usage

```
#define FROM 64
#define TO_E 5      // Exponent
#define TO_M 21     // Mantissa

double f(double x, double y) {
    return ...;
}

double a = 3, b = 4;

// Step 1: Call w
//         Here w
//         as sto
a = __enzyme_trun
b = __enzyme_trun

// Step 2: Genera
//         with o
double res = __en

// Step 3: Conver
res = __enzyme_expand_mem_value(res, FROM, TO_E, TO_M);
```

You can also specify on the command line:

```
clang ... --enzyme-truncate-all="64to5-21"
```

For full-module effect

Future Work & Conclusions

- Being aware of the floating point representation used is critical to both performance and accuracy!
- Optimizing floating point choices inherently requires understanding the impact of normal compiler optimization
- Our tool builds off Enzyme/LLVM to automatically retune floats alongside optimization without programmer rewriting
- Future work:
  - Combine with program analysis to determine which operations requiring tuning, and by what amount
  - Tune only individual parts of a function but leave other parts at full precision
  - Consider other sources of error than floating point
- All open source (https://github.com/EnzymeAD/Enzyme), please reach out if interested!