Universal Numbers Library: Multi-format Variable Precision Arithmetic Library

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Software

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Summary

Universal Numbers Library, or simply *Universal*, is a comprehensive, self-contained C++ header-only template library that provides implementations of various number representations and standard arithmetic operations on arbitrary configurations of integer and real numbers (Omtzigt et al., 2020). With its extensive collection of number systems, including integers, decimals, fixed-points, rationals, linear floats, tapered floats, logarithmic, SORNs, interval, level-index, and adaptive-precision binary and decimal integers and floats, Universal offers a robust verification suite for each system.

Using a posit number as an example, the basic pattern to use a custom *Universal* type is:

```cpp
#include <universal/number/posit/posit.hpp>

template<typename Real>
Real MyKernel(const Real& a, const Real& b) {
    return a * b;  // replace this with your kernel computation
}

constexpr double pi = 3.14159265358979323846;

int main() {
    using Real = sw::universal::posit<32,2>;

    Real a = sqrt(2);
    Real b = pi;
    std::cout << "Result: " << MyKernel(a, b) << std::endl;
}
```

Universal delivers software and hardware co-design capabilities to develop low and mixed-precision algorithms for reducing energy consumption in signal processing, Industry 4.0, machine learning, robotics, and high-performance computing applications (Omtzigt & Quinlan, 2022). The package includes command-line tools for visualizing and interrogating numeric encodings, an interface for setting and querying bits, and educational examples showcasing performance gain and numerical accuracy with the different number systems. Finally, Docker containers are available to experiment with the library without cloning the repo and building the source code.

```
$ docker pull stillwater/universal
$ docker run -it --rm stillwater/universal bash
```

Universal was originally established in 2017 as a reference implementation of the evolving unum Type III (posit and valid) standard for bit-level arithmetic. However, as the demand for supporting a diverse range of number systems grew, *Universal* evolved into a complete platform for numerical analysis and computational mathematics, capable of solving problems such as large factorials using adaptive-precision integers and serving as Oracles using adaptive-precision floats. Many projects have leveraged *Universal*, including the Matrix Template Library (MTL4), Geometry + Simulation Modules (G+SMO), Bembel (a fast IGA BEM solver), and the Odeint ODE solver.

The default build configuration will produce the command line tools, a playground, and educational and application examples. It is also possible to construct the full regression suite across all the number systems. For instance, the shortened output for the commands `single` and `single 1.23456789` are below.

```
$ single
min exponent                                           -125
max exponent                                            128
radix                                                     2
radix digits                                             24
min                                             1.17549e-38
max                                             3.40282e+38
lowest                                         -3.40282e+38
epsilon (1+1ULP-1)                              1.19209e-07
round_error                                             0.5
denorm_min                                       1.4013e-45
infinity                                                inf
quiet_NAN                                               nan
signaling_NAN                                           nan
...


$ single 1.23456789
scientific   : 1.2345679
triple form  : (+,0,0b00111100000011001010010)
binary form  : 0b0.0111'1111.001'1110'0000'0110'0101'0010
color coded  : 0b0.0111'1111.001'1110'0000'0110'0101'0010
```

Statement of need

The demand for high-performance computing (HPC), machine learning, and deep learning has grown significantly in recent years (e.g., Carmichael et al., 2019; Cococcioni et al., 2022; Desrentes et al., 2022), leading to increased environmental impact and financial cost due to their high energy consumption for storage and processing (Haidar, Abdelfattah, et al., 2018). To address these challenges, researchers are exploring ways to reduce energy consumption through redesigning algorithms and minimizing data movement and processing. The use of multi-precision arithmetic in hardware is also becoming more prevalent (Haidar, Tomov, et al., 2018). NVIDIA has added support for low-precision formats in its GPUs to perform tensor operations (Choquette et al., 2021), including a 19-bit format with an 8-bit exponent and 10-bit mantissa (see also (Intel Corporation, 2018; Kharya, 2020). Additionally, Google has developed the "Brain Floating Point Format," known as "bfloat16," which enables the training and operation of deep neural networks using Tensor Processing Units (TPUs) at higher performance and lower cost (Wang & Kanwar, 2019). This trend towards low-precision numerics is driving the redesign of many standard algorithms, particularly in the field of energy-efficient linear solvers, which is a rapidly growing area of research (Carson & Higham, 2018; Haidar et al., 2017; Haidar, Tomov, et al., 2018; Haidar, Abdelfattah, et al., 2018; Higham et al., 2019).

While the primary motivation for low-precision arithmetic is its high performance and energy efficiency, mixed-precision algorithm designs aim to identify and exploit opportunities to rightsize the number system used for critical computational paths representing the execution bottleneck. Furthermore, when these algorithms are incorporated into embedded devices and custom hardware engines, we approach optimal performance and power efficiency. Therefore, investigations into computational mathematics and measuring mixed-precision algorithms' accuracy, efficiency, robustness, and stability are needed.

Custom number systems that optimize the entire system's performance are crucial components to imbue embedded systems with more autonomy. Likewise, energy efficiency is an essential differentiator for embedded intelligence applications. By observing distinct arithmetic requirements of the control and data flow, many performance and power efficiency gains can be achieved when developing unique compute solutions. It is essential to consider the precision requirements and the necessary dynamic range of arithmetic operations when optimizing these compute engines.

Verification Suite

Each number system contained within *Universal* is supported by a comprehensive verification environment testing library class API consistency, logic and arithmetic operators, the standard math library, arithmetic exceptions, and language features such as compile-time constexpr. The verification suite is run as part of the `make test` command in the build directory.

Due to the size of the library, the build system for *Universal* allows for fine-grain control to subset the test environment for productive development and verification. There are twelve core build category flags defined:

- BUILD_APPLICATIONS
- BUILD_BENCHMARKS
- BUILD_CI
- BUILD_CMD_LINE_TOOLS
- BUILD_C_API
- BUILD_DEMONSTRATION
- BUILD_EDUCATION
- BUILD_LINEAR_ALGEBRA
- BUILD_MIXEDPRECISION_SDK
- BUILD_NUMBERS
- BUILD_NUMERICS
- BUILD_PLAYGROUND

The flags, when set during cmake configuration, i.e., `cmake -DBUILD_CI=ON ..`, enable build targets specialized to the category. For example, the `BUILD_CI` flag turns on the continuous integration regression test suites for all number systems, and the `BUILD_APPLICATIONS` flag will build all the example applications that provide demonstrations of mixed-precision, high-accuracy, reproducible and/or interval arithmetic.

Each build category contains individual targets that further refine the build targets. For example, `cmake -DBUILD_NUMBER_POSIT=ON -DBUILD_DEMONSTRATION=OFF ..` will build just the fixed-size, arbitrary configuration posit number system regression environment.

It is also possible to run specific test suite components, for example, to validate algorithmic changes to more complex arithmetic functions, such as square root, exponent, logarithm, and trigonometric functions. Here is an example, assuming that the logarithmic number system has been configured during the cmake build generation:

```
$ make lns_trigonometry
```

The repository's README file has all the details about the build and regression environment and how to streamline its operation.

Availability and Documentation

Universal Number Library is available under the MIT License. The package may be cloned or forked from the GitHub repository. Documentation is provided via `docs`, including a tutorial introducing primary functionality and detailed reference and communication networks. The library employs extensive unit testing.

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