

# ZpL: a $p$ -adic precision package

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## ABSTRACT

We present a new package `ZpL` for the mathematical software system `SAGEMATH`. It implements a sharp tracking of precision on  $p$ -adic numbers, following the theory of ultrametric precision introduced in [4]. The underlying algorithms are mostly based on automatic differentiation techniques. We introduce them, study their complexity and discuss our design choices. We illustrate the benefits of our package (in comparison with previous implementations) with a large sample of examples coming from linear algebra, commutative algebra and differential equations.

## CCS CONCEPTS

• Computing methodologies → Algebraic algorithms;

## KEYWORDS

Algorithms,  $p$ -adic precision, Automatic Differentiation

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## 1 INTRODUCTION

When computing with real and  $p$ -adic fields, exact results are usually impossible, since most elements have infinite decimal or  $p$ -adic expansions. Working with these fields thus requires an analysis of how precision evolves through the sequence of steps involved in carrying out a computation. Such analysis can be carried out automatically by the software, or via theorems specific to a particular application [10, 12]. In this paper, we describe a package for computing with  $p$ -adic rings and fields [15], based on a series of papers by the same authors [4–7]. The core of the package is a method for tracking precision using  $p$ -adic lattices which can yield dramatically more precise results than traditional methods, at the cost of increased runtime and memory usage.

The standard method for handling precision when computing with real numbers is floating point arithmetic, which may also be used in  $p$ -adic computation. At a given precision level, a finite set of representable numbers are chosen, and arithmetic operations are defined to give a representable number that is close to the

true result [1]. Floating point arithmetic has the benefit of efficient arithmetic operations, but users are responsible for tracking the precision of the results. Numerically unstable algorithms can lead to very inaccurate answers [9].

If provably correct results are desired, interval arithmetic provides an alternative to floating point. Instead of just tracking an approximation to the answer, one also tracks a radius within which the true result lies. This method is commonly used for  $p$ -adic computations since the ultrametric property of  $p$ -adic fields frequently keeps the radius small. Computations remain fairly efficient with this approach, but numerical instability can still lead to dramatic losses in precision (see §2 for many examples). Tracking the precision of multiple variables concurrently, the set of possible true values associated to an inexact value takes the form of an ellipsoid with axes parallel to the coordinate axes.

For better control of precision, we may allow arbitrary axes. This change would have little utility for real numbers, since such ellipsoids are not preserved by most functions. For  $p$ -adic fields, in contrast, differentiable maps with surjective differential will send sufficiently small ellipsoids to other ellipsoids. From an algebraic perspective, these ellipsoids are just cosets of a lattice  $H$  inside a  $p$ -adic vector space, and the main result of [4] (see also Proposition 3.1 below) describes how the image of such a coset under a map  $f$  is given exactly by applying the differential of  $f$  to  $H$ .

In this paper, we describe an implementation of this idea in `SAGEMATH` [14]. Rather than attaching a precision to each element, we store the precision of many elements together by tracking a precision module<sup>1</sup> for the whole collection of variables. As variables are created and destroyed, we update a matrix whose rows represent the vectors in the module. Information about the precision of elements is extracted from the matrix as necessary. Concretely, our package provides two new `SAGEMATH` parents<sup>2</sup>, namely `ZpLC` and `ZpLF` (and their fraction fields `QpLC` and `QpLF`). The acronyms LC and LF stand for “lattice-cap” and “lattice-float” respectively (see §3 for details). Our package has been included in the standard distribution of `SAGEMATH` since version 8.2.

The article is structured as follows. In §2 we provide a demonstration of the package, showing how it can provide more precise answers than the traditional methods for tracking  $p$ -adic precision. In particular, §2.1 describes elementary arithmetic and the SOMOS-4 sequence, §2.2 gives examples from linear algebra, §2.3 examples using polynomials, and §2.4 examples of differential equations. In §3 we give more details on the implementation. §3.1 contains a brief overview on the theory of  $p$ -adic precision of [4]. §3.2 is devoted to the implementation of automatic differentiation leading to the

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<sup>1</sup>Throughout the paper, the word “module” has its mathematical meaning: it denotes an additive group endowed with an external product by scalars in  $\mathbb{Z}_p$ .

<sup>2</sup>Parents in `SAGEMATH` are the analogues of container objects in computer science. Basically a parent corresponds to an implementation of a concrete mathematical structure, as the ring of  $p$ -adic integers.

actual computation of the module that models the precision. In §3.3, we explain how precision on any individual number can be recovered and discuss the validity of our results. The complexity overhead induced by our package is analyzed in §3.4. Finally, §4 contains a discussion of how we see this package fitting into the existing  $p$ -adic implementations. While these methods do introduce overhead, they are well suited to exploring precision behavior when designing algorithms, and can provide hints as to when further precision analysis would be useful.

## 2 SHORT DEMONSTRATION

The first step is to define the parents: the rings of  $p$ -adic numbers we will work with.

```
In: Z2 = ZpXX(2, print_mode='digits')
    Q2 = QpXX(2, print_mode='digits')
```

`ZpXX` is a generic notation for `ZpCR`, `ZpLC` and `ZpLF`. The first, `ZpCR`, is the usual constructor for  $p$ -adic parents in SAGEMATH. It tracks precision using interval arithmetic. The parents `ZpLC` and `ZpLF` provided by our package track precision differently; more details will be provided in Section 3. In the sequel, we will compare the outputs provided by each parent. As the results for `ZpLF` and `ZpLC` agree on all examples in this section, we will only give those for `ZpLC`.

In what follows, random elements in  $\mathbb{Z}_p$  are always picked with respect to the Haar measure. Random elements in  $\mathbb{Q}_p$  are constructed as a product  $p^V \cdot U$  where  $U$  is a random element in  $\mathbb{Z}_p$  (distributed according to the Haar measure) and  $V$  is a random variable taking values in  $\mathbb{Z}$  which is independent from  $U$  and distributed as follows:

$$\text{Prob}[V=0] = \frac{1}{5}, \quad \text{Prob}[V=v] = \frac{2}{5^{|v|} \cdot (|v|+1)}, \quad \forall v \neq 0.$$

This distribution is the default in SAGEMATH, and the function `random_element` used below picks the same element for each of `ZpCR`, `ZpLC` and `ZpLF`.

### 2.1 Elementary arithmetic

We begin our tour of the `ZpL` package with some basic arithmetic. Elements are approximated by giving a valuation and a unit, where the unit is specified modulo a power of  $p$  determined by the global lattice precision.

```
In: x = random_element(Z3, prec=5); x
ZpCR: ...11111
ZpLC: ...11111
```

Multiplication by  $p$  (here 3) is a shift on the digits and thus leads to a gain of one digit in absolute precision. In the example below, we observe that when this multiplication is split into several steps, `ZpCR` does not see the gain of precision while `ZpL` does.

```
In: 3*x          In: x + x + x
ZpCR: ...111110  ZpCR: ...111110
ZpLC: ...111110  ZpLC: ...111110
```

The same phenomenon occurs for multiplication.

```
In: x^3          In: x * x * x
ZpCR: ...010101  ZpCR: ...10101
ZpLC: ...010101  ZpLC: ...010101
```

`ZpL` is also well suited for working with coefficients with unbalanced precision.

```
In: x = random_element(Z2, prec=10)
    y = random_element(Z2, prec=5)
In: u, v = x+y, x-y
    u, v
ZpCR: (...10111, ...01111)
ZpLC: (...10111, ...01111)
```

Now, let us compute  $u + v$  and compare it with  $2x$  (observe that they should be equal).

```
In: u + v          In: 2*x
ZpCR: ...00110     ZpCR: ...00110100110
ZpLC: ...00110100110  ZpLC: ...00110100110
```

Again `ZpCR` does not output the optimal precision when the computation is split into several steps whereas `ZpL` does. These basic examples illustrate situations that occur during the execution of many algorithms. As a result, interval arithmetic frequently overestimates the loss of precision. The aim of our package is to reduce this precision loss. In the next subsections, we present a bunch of examples showing the benefit of `ZpL` in various contexts.

**SOMOS 4.** A first example is the SOMOS-4 sequence. It is defined by the recurrence:

$$u_{n+4} = \frac{u_{n+1}u_{n+3} + u_{n+2}^2}{u_n}$$

and is known for its high numerical instability (see [4]). Nevertheless, the `ZpL` package saves precision even when using a generic unstable implementation of the SOMOS iteration.

```
In: def somos4(u0, u1, u2, u3, n):
    a, b, c, d = u0, u1, u2, u3
    for _ in range(4, n+1):
        a, b, c, d = b, c, d, (b*d + c*c) / a
    return d
In: u0 = u1 = u2 = Z2(1,15); u3 = Z2(3,15)
    somos4(u0, u1, u2, u3, 18)
ZpCR: ...11
ZpLC: ...100000000000111
In: somos4(u0, u1, u2, u3, 100)
ZpCR: PrecisionError: cannot divide by something
indistinguishable from zero.
ZpLC: ...001001001110001
```

### 2.2 Linear algebra

Many generic algorithms of linear algebra exhibit instability when used with  $p$ -adic numbers. Our package `ZpL` frequently eliminates this instability without having to change either the algorithm or the implementation.

**Matrix multiplication.** As revealed in [5], a first simple example where instability appears is simply matrix multiplication. This might be surprising because no division occurs in this situation. Observe nevertheless the difference between `ZpCR` and `ZpLC`.

```
In: MS = MatrixSpace(Z2, 2)
    M = random_element(MS, prec=5)
    for _ in range(25):
        M *= random_element(MS, prec=5)
M
ZpCR: [0 0]
      [0 0]
ZpLC: [...100000000000 ...1000000000]
      [...0100000000 ...001000000]
```

On the aforementioned example, we notice that `ZpCR` is unable to decide whether the product vanishes or not. Having good estimates on the precision is therefore very important in such situations.

**Characteristic polynomials.** Characteristic polynomials are notoriously hard to compute [5, 7]. By default, `SAGEMATH` uses a division-free algorithm over  $\mathbb{Q}_p$ , this choice is not enough to achieve optimal precision in the `QpCR` case since negative valuations may appear. We illustrate the different precision behavior in the following example.

```
In: M = random_element(MatrixSpace(Q2,3), prec=10)
M.determinant()
QpCR: ...010000010
QpLC: ...010000010
In: M.charpoly()
QpCR: ...000000000000000001*x^3 +
...1001011.011*x^2 + ...0111.01*x + 0
QpLC: ...000000000000000001*x^3 +
...1001011.011*x^2 + ...11100111.01*x +
...010000010
```

We observe that `ZpLC` can guarantee 4 more digits on the  $x$  coefficient. Moreover, it recovers the correct precision on the constant coefficient (which is the determinant) whereas `ZpCR` is confused and cannot even certify that it does not vanish.

### 2.3 Commutative algebra

Our package can be applied to computation with  $p$ -adic polynomials.

**Euclidean algorithm.** A natural example is that of the computation of GCD in the Euclidean ring  $\mathbb{Q}_p[X]$ , whose stability has been studied in [3]. A naive implementation of the Euclidean algorithm can produce different behavior depending on the type of implementation of the field of  $p$ -adic coefficients.

```
In: S.<x> = PolynomialRing(Z2)
P = random_element(S, degree=10, prec=5)
Q = random_element(S, degree=10, prec=5)
D = x^5 + random_element(S, degree=4, prec=8); D
ZpCR: ...000000000000000001*x^5 + ...11111010*x^4 +
...10000000*x^3 + ...11001111*x^2 +
...10000110*x + ...11100010
ZpLC: ...000000000000000001*x^5 + ...11111010*x^4 +
...10000000*x^3 + ...11001111*x^2 +
...10000110*x + ...11100010
In: def euclidean(A,B):
while B != 0:
A, B = B, A % B
return A.monic()
euclidean(D*P, D*Q)
ZpCR: 0*x^9 + ...1*x^8 + 0*x^7 + 0*x^6 + 0*x^5 +
0*x^4 + 0*x^3 + ...1*x^2 + ...10*x + ...10
ZpLC: ...000000000000000001*x^5 + ...11111010*x^4 +
...10000000*x^3 + ...11001111*x^2 +
...10000110*x + ...11100010
```

With high probability,  $P$  and  $Q$  are coprime, implying that the gcd of  $DP$  and  $DQ$  is  $D$ . However, we observe that `ZpCR` output a quite different result. The point is that, in the `ZpCR` case, Euclidean algorithm stops prematurely because the test  $B \neq 0$  fails too early due to the lack of precision.

**Gröbner bases.** Our package can be applied on complex computations like that of Gröbner bases using generic Gröbner bases algorithms.

```
In: R.<x,y,z> = PolynomialRing(Q2, order='invlex')
F = [ Q2(2,10)*x + Q2(1,10)*z,
Q2(1,10)*x^2 + Q2(1,10)*y^2 - Q2(2,10)*z^2,
Q2(4,10)*y^2 + Q2(1,10)*y*z + Q2(8,10)*z^2 ]
In: from sage.rings.polynomial.toy_buchberger\
import buchberger_improved
g = buchberger_improved(ideal(F))
g.sort(); g
QpCR: [x^3, x*y + ...1100010*x^2,
y^2 + ...11001*x^2, z + ...0000000010*x]
QpLC: [x^3, x*y + ...111100010*x^2,
y^2 + ...111111001*x^2, z + ...0000000010*x]
```

As we can see, some loss in precision occurs in the Buchberger algorithm and is avoided thanks to `ZpL`.

### 2.4 $p$ -adic differential equations

In [11], the authors studied the computation of isogenies between elliptic curves over finite fields by applying the lattice precision model to  $p$ -adic differential equations. Specifically, they considered the equation  $y' = g(x) \times h(y)$  with  $g, h, y \in \mathbb{Z}_p[[x]]$  such that  $g(0) = h(0) = 1$  and  $y(0) = 0$ .

Their main result was that the intrinsic loss in precision when computing the coefficient  $x^n$  of  $y$  from  $g$  and  $h$  was in  $\log_p(n)$  even though a naive analysis of the Newton method for solving the equation yields a loss in  $\log_p(n)^2$ .

We can reach this theoretical loss in precision using `ZpL`, while `ZpCR` does not perform as well. We apply  $N$  steps of the Newton method for  $y' = g \times h(y)$  as described in [11], using a generic `Newton_Iteration_Solver(g, h, N)`.

```
In: S.<t> = PowerSeriesRing(Q2, 16)
h = 1 + t + t^3
y = t + t^2 * random_element(S, prec=10)
g = y.derivative() / h(y)
u = Newton_Iteration_Solver(g, h, 4); u[15]
QpCR: ...1101
QpLC: ...11011101
```

## 3 BEHIND THE SCENES

In this section, we explain how our package `ZpL` works and analyze its performance. The main theoretical result on which our package is based is the ultrametric precision theory developed in [4], which suggests tracking precision *via* lattices and differential computations. For this reason, our approach is very inspired by automatic differentiation techniques [13] and our implementation follows the usual operator overloading strategy. We will introduce two versions of our package, namely `ZpLC` and `ZpLF`: this former is safer while the latter is faster.

*Remark about the naming.* The letter L, which appears in the name of the package, comes from “lattices”. The letters C (in `ZpLC`) and F (in `ZpLF`) stand for “cap” and “float” respectively.

### 3.1 The precision Lemma

In [4], we suggest the use of lattices to represent the precision of elements in  $\mathbb{Q}_p$ -vector spaces. This approach contrasts with the

*coordinate-wise method* (of e.g.  $\mathbb{Z}_p(5)$ ) that is traditionally used in SAGEMATH where the precision of an element is specified by giving the precision of each coordinate separately and is updated after each basic operation.

Consider a finite dimensional normed vector space  $E$  defined over  $\mathbb{Q}_p$ . We use the notation  $\|\cdot\|_E$  for the norm on  $E$  and  $B_E^-(r)$  (resp.  $B_E(r)$ ) for the open (resp. closed) ball of radius  $r$  centered at the origin. A lattice  $L \subset E$  is a sub- $\mathbb{Z}_p$ -module which generates  $E$  over  $\mathbb{Q}_p$ . Because of ultrametricity, the balls  $B_E(r)$  and  $B_E^-(r)$  are examples of lattices. Lattices can be thought of as special neighborhoods of 0, and therefore are good candidates to model precision data. Moreover, as revealed in [4], they behave quite well under (strictly) differentiable maps:

**PROPOSITION 3.1.** *Let  $E$  and  $F$  be two finite dimensional normed vector spaces over  $\mathbb{Q}_p$  and  $f : U \rightarrow F$  be a function defined on an open subset  $U$  of  $E$ . We assume that  $f$  is differentiable at some point  $v_0 \in U$  and that the differential  $df_{v_0}$  is surjective. Then, for all  $\rho \in (0, 1]$ , there exists a positive real number  $\delta$  such that, for all  $r \in (0, \delta)$ , any lattice  $H$  such that  $B_E^-(\rho r) \subset H \subset B_E(r)$  satisfies:*

$$f(v_0 + H) = f(v_0) + df_{v_0}(H). \quad (1)$$

This proposition enables the *lattice method* of tracking precision, where the precision of the input is specified as a lattice  $H$  and precision is tracked via differentials of the steps within a given algorithm. The equality sign in Eq. (1) shows that this method yields the optimum possible precision. We refer to [4, §4.1] for a more complete exposition.

### 3.2 Tracking precision

We now explain in more details the internal mechanisms **ZpLC** and **ZpLF** use for tracking precision.

In what follows, it will be convenient to use a notion of discrete time represented by the letter  $t$ . Rigorously, it is defined as follows:  $t = 0$  when the  $p$ -adic ring **ZpLC**( $\dots$ ) or **ZpLF**( $\dots$ ) is created and increases by 1 each time a variable is created, deleted<sup>3</sup> or updated.

Let  $\mathcal{V}_t$  be the set of alive variables at time  $t$ . Set  $E_t = \mathbb{Q}_p^{\mathcal{V}_t}$ ; it is a finite dimensional vector space over  $\mathbb{Q}_p$  which should be thought of as the set of all possible values that can be taken by the variables in  $\mathcal{V}_t$ . For  $v \in \mathcal{V}_t$ , let  $e_v \in E_t$  be the vector whose coordinates all vanish except at position  $v$  which takes the value 1. The family  $(e_v)_{v \in \mathcal{V}_t}$  is obviously a basis of  $E_t$ ; we will refer to it as the *canonical basis*.

**3.2.1 The case of ZpLC.** Following Proposition 3.1, the package **ZpLC** follows the precision by keeping track of a lattice  $H_t$  in  $E_t$ , which is a global object whose purpose is to model the precision on all the variables in  $\mathcal{V}_t$  all together. Concretely, this lattice is represented by a matrix  $M_t$  in row-echelon form whose rows form a set of generators. Below, we explain how the matrices  $M_t$  are updated each time  $t$  increases.

*Creating a variable.* This happens when we encounter an instruction having one of the two following forms:

$$\begin{array}{ll} \text{[Computation]} & w = f(v_{-1}, \dots, v_{-n}) \\ \text{[New value]} & w = R(\text{value}, \text{prec}) \end{array}$$

<sup>3</sup>The deletion can be explicit (through a call to the `del` operator) or implicit (handled by the garbage collector).

In both cases,  $w$  is the newly created variable. The  $v_i$ 's stand for already defined variables and  $f$  is some  $n$ -ary builtin function (in most cases it is just addition, subtraction, multiplication or division). On the contrary, the terms "value" and "prec" refer to user-specified constants or integral values which were computed earlier.

Let us first examine the first construction [Computation]. With our conventions, if  $t$  is the time just before the execution of the instruction we are interested in, the  $v_i$ 's lie in  $\mathcal{V}_t$  while  $w$  does not. Moreover  $\mathcal{V}_{t+1} = \mathcal{V}_t \sqcup \{w\}$ , so that  $E_{t+1} = E_t \oplus \mathbb{Q}_p e_w$ . The mapping taking the values of variables at time  $t$  to that at time  $t+1$  is:

$$\begin{array}{ll} F : E_t & \longrightarrow E_{t+1} \\ \underline{x} & \longmapsto \underline{x} \oplus f(x_1, \dots, x_n) \end{array}$$

where  $x_i$  is the  $v_i$ -th coordinate of the vector  $\underline{x}$ . The Jacobian matrix of  $F$  at  $\underline{x}$  is easily computed; it is the block matrix  $J_{\underline{x}}(F) = \begin{pmatrix} I & L \end{pmatrix}$  where  $I$  is the identity matrix of size  $\text{Card } \mathcal{V}_t$  and  $L$  is the column vector whose  $v$ -th entry is  $\frac{\partial f}{\partial v}(\underline{x})$  if  $v$  is one of the  $v_i$ 's and 0 otherwise. Therefore, the image of  $H_t$  under  $dF_{\underline{x}}$  is represented by the matrix  $J_{\underline{x}}(F) \cdot M_t = \begin{pmatrix} M_t & C \end{pmatrix}$  where  $C$  is the column vector:

$$C = \sum_{i=1}^n \frac{\partial f}{\partial v_i}(\underline{x}) \cdot C_i \quad (2)$$

where  $C_i$  is the column vector of  $M_t$  corresponding to the variable  $v_i$ . Observe that the matrix  $J_{\underline{x}}(F) \cdot M_t$  is no longer a square matrix; it has one extra column. This reflects the fact that  $\dim E_{t+1} = \dim E_t + 1$ . Rephrasing this in a different language, the image of  $H_t$  under  $dF_{\underline{x}}$  is no longer a lattice in  $E_{t+1}$  but is included in an hyperplane, violating our definition of a precision lattice.

The package **ZpLC** tackles this issue by introducing a cap, analogous to adding  $O(p^N)$  when creating a  $p$ -adic number from an integer. Specifically, we choose an integer  $N_{t+1}$  and replace the  $\mathbb{Z}_p$ -submodule  $dF_{\underline{x}}(H_t)$  with the lattice  $H_{t+1} = dF_{\underline{x}}(H_t) \oplus p^{N_{t+1}} \mathbb{Z}_p e_w$ . Alternatively, one may introduce the map:

$$\begin{array}{ll} \tilde{F} : E_t \oplus \mathbb{Q}_p & \longrightarrow E_{t+1} \\ \underline{x} \oplus c & \longmapsto \underline{x} \oplus (f(x_1, \dots, x_n) + c). \end{array} \quad (3)$$

The lattice  $H_{t+1}$  is then the image of  $H_t \oplus p^{N_{t+1}} \mathbb{Z}_p$  under  $d\tilde{F}_{(\underline{x}, \star)}$  for any value of  $\star$ . In order to carry out this strategy, one must choose  $N_{t+1}$ . We do so by associating two constants to each ring: a relative cap **RELCAP** and an absolute cap **ABSCAP**. We then set

$$N_{t+1} = \min(\text{ABSCAP}, \text{RELCAP} + v_p(y)) \quad (4)$$

with  $y = f(x_1, \dots, x_n)$ . Larger caps mean that the precision of the final result is less likely to be affected, but require more space. See Remark 3.2 for more details.

In concrete terms, the lattice  $H_{t+1}$  is represented by the block matrix:

$$\begin{pmatrix} M_t & C \\ 0 & p^{N_{t+1}} \end{pmatrix}.$$

Performing row operations, we see then that the entries of  $C$  can be reduced modulo  $p^{N_{t+1}}$  without changing the lattice. In order save space, we perform this reduction and define  $M_{t+1}$  by:

$$M_{t+1} = \begin{pmatrix} M_t & C \bmod p^{N_{t+1}} \\ 0 & p^{N_{t+1}} \end{pmatrix}.$$



We observe in particular that  $M_{t+1}$  is still in row-echelon form.

Finally, we need to explain which value is set to the newly created variable  $w$ . We observe that it cannot be exactly  $f(x_1, \dots, x_n)$  because the latter is *a priori* a  $p$ -adic number which cannot be computed exactly. For this reason, we have to truncate it at some finite precision. Again we choose the precision  $O(p^{N_{t+1}})$ , i.e. we define  $x_w$  as  $f(x_1, \dots, x_n) \bmod p^{N_{t+1}}$ . The congruence  $\bar{x} \oplus f(x_1, \dots, x_n) \equiv \bar{x} \oplus x_w \pmod{H_{t+1}}$  (which holds thanks to the extra generator we have added) justifies this choice.

The second construction “ $w = R(\text{value}, \text{prec})$ ” is easier to handle since, roughly speaking, it corresponds to the case  $n = 0$ . In this situation, keeping in mind the cap, the lattice  $H_{t+1}$  is defined by  $H_{t+1} = H_t + p^{\min(\text{prec}, N_{t+1})} \mathbb{Z}_p e_w$  for the cap  $N_{t+1} = \min(\text{ABSCAP}, \text{RELCAP} + v_p(\text{value}))$ . The corresponding matrix  $M_{t+1}$  is then given by:

$$M_{t+1} = \begin{pmatrix} M_t & 0 \\ 0 & p^{\min(\text{prec}, N_{t+1})} \end{pmatrix}.$$

*Deleting a variable.* Let us now examine the case where a variable  $w$  is deleted (or collected by the garbage collector). Just after the deletion, at time  $t+1$ , we then have  $\mathcal{V}_{t+1} = \mathcal{V}_t \setminus \{w\}$ . Thus  $E_t = E_{t+1} \oplus \mathbb{Q}_p e_w$ . Moreover, the deletion of  $w$  is modeled by the canonical projection  $f : E_t \rightarrow E_{t+1}$ . Since  $f$  is linear, it is its own differential (at each point) and we set  $H_{t+1} = f(H_t)$ . A matrix representing  $H_{t+1}$  is deduced from  $M_t$  by erasing the column corresponding to  $w$ . However the matrix we get this way is no longer in row-echelon form. We then need to re-echelonize it.

More precisely, the obtained matrix has this shape:

where a cell is colored when it can contain a non-vanishing entry. The top part of the matrix is then already echelonized, so that we only have to re-echelonize the bottom right corner whose size is the distance from the column corresponding to the erased variable to the end. Thanks to the particular shape of the matrix, the echelonization can be performed efficiently: we combine the first rows (of the bottom right part) in order to clear the first unwanted nonzero entry and then proceed recursively.

*Updating a variable.* Just like for creation, this happens when the program reaches an affectation “ $w = \dots$ ” where the variable  $w$  is already defined. This situation reduces to the creation of the temporary variable (the value of the right-hand-side), the deletion of the old variable  $w$  and a renaming. It can then be handled using the methods discussed previously.

**3.2.2 The case of ZpLF.** The way the package ZpLF tracks precision is based on similar techniques but differs from ZpLC in that it does not introduce a cap but instead allows  $H_t$  to be a sub- $\mathbb{Z}_p$ -module of  $E_t$  of any codimension. This point of view is nice because it implies smaller objects and consequently leads to faster

algorithms. However, it has a huge drawback; indeed, unlike lattices, submodules of  $E_t$  of arbitrary codimensions are *not* exact objects, in the sense that they cannot be represented by integral matrices in full generality. Consequently, they cannot be encoded on a computer. We work around this drawback by replacing everywhere exact  $p$ -adic numbers by floating point  $p$ -adic numbers (at some given relative precision  $k$ ) [2]. In the floating point model, we approximate all numbers in the disc  $p^v(u + O(p^k))$  by a single rational number  $p^v u$ . Operations on these numbers are then not exact, but instead produce the representative in the correct disc.

The fact that the lattice  $H_t$  can now have arbitrary codimension translates to the fact the matrix  $M_t$  can be rectangular. Precisely, we will maintain matrices  $M_t$  of the shape:

where only the colored cells may contain a nonzero value and the black cells—the so-called *pivots*—do not vanish. A variable whose corresponding column contains a pivot will be called a *pivot variable* at time  $t$ .

*Creating a variable.* We assume first that the newly created variable is defined through a statement of the form: “ $w = f(v_{-1}, \dots, v_{-n})$ ”. As already explained in the case of ZpLC, this code is modeled by the mathematical mapping:

$$\begin{aligned} F : E_t &\longrightarrow E_{t+1} \\ \underline{x} &\longmapsto \underline{x} \oplus f(x_1, \dots, x_n). \end{aligned}$$

Here  $\underline{x}$  represents the state of memory at time  $t$ , and  $x_i$  is the coordinate of  $\underline{x}$  corresponding to the variable  $v_i$ .

In the ZpLF framework,  $H_{t+1}$  is defined as the image of  $H_t$  under the differential  $dF_{\underline{x}}$ . Accordingly, the matrix  $M_{t+1}$  is defined as  $M_{t+1} = (M_t \ C)$  where  $C$  is the column vector defined by Eq. (2). However, since operations defining  $M_{t+1}$  are performed with floating point numbers, the matrix  $M_{t+1}$  gives only an approximate basis for  $H_{t+1}$ .

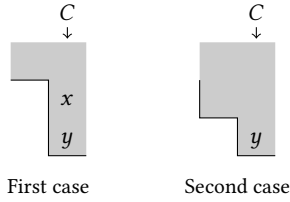
If  $w$  is created by the code “ $w = R(\text{value}, \text{prec})$ ”, we define  $H_{t+1} = H_t \oplus p^{\text{prec}} \mathbb{Z}_p e_w$  and consequently:

$$M_{t+1} = \begin{pmatrix} M_t & 0 \\ 0 & p^{\text{prec}} \end{pmatrix}$$

If  $\text{prec}$  is  $+\infty$  (or, equivalently, not specified), we agree that  $H_{t+1} = H_t$  and  $M_{t+1} = (M_t \ 0)$ .

*Deleting a variable.* As for ZpLC, the matrix operation implied by the deletion of the variable  $w$  is the deletion of the corresponding column of  $M_t$ . If  $w$  is not a pivot variable at time  $t$ , the matrix  $M_t$  keeps the form (5) after erasure; therefore no more treatment is needed in this case.

Otherwise, we re-echelonize the matrix as follows. After the deletion of the column  $C_w$ , we examine the first column  $C$  which was located on the right of  $C_w$ . Two situations may occur (depending on the fact that  $C$  was or was not a pivot column):



In the first case, we perform row operations in order to replace the pair  $(x, y)$  by  $(d, 0)$  where  $d$  is an element of valuation  $\min(v_p(x), v_p(y))$ . Observe that  $y$  is necessarily nonzero in this case, so that  $d$  does not vanish as well. After this operation, we move to the next column and repeat the same process.

The second case is divided into two subcases. First, if  $y$  does not vanish, it can serve as a pivot and the obtained matrix has the desired shape. When this occurs, the echelonization stops. On the contrary, if  $y = 0$ , we just tint the corresponding cell and move to the next column without modifying the matrix.

### 3.3 Visualizing the precision

Our package implements several methods giving access to the precision structure. In the subsection, we present and discuss the most relevant features in this direction.

**Absolute precision of one element.** This is the simplest accessible precision datum. It is encapsulated in the notation when an element is printed. For example, the (partial) session:

```
In: v = ZZ(173, 10); v
ZpLC: ...00101011101
```

indicates that the absolute precision on  $v$  is 10 since exactly 10 digits are printed. The method `precision_absolute` provides an easier-to-use access to the absolute precision.

```
In: v.precision_absolute()
ZpLC: 10
```

Both `ZpLC` and `ZpLF` compute the absolute precision of  $v$  (at time  $t$ ) as the smallest valuation of an entry of the column of  $M_t$  corresponding to the variable  $v$ . Alternatively, it is the unique integer  $N$  for which  $\pi_v(H_t) = p^N \mathbb{Z}_p$  where  $\pi_v : E_t \rightarrow \mathbb{Q}_p$  takes a vector to its  $v$ -coordinate. This definition of the absolute precision sounds relevant because, if we believe that the submodule  $H_t \subset E_t$  is supposed to encode the precision on the variables in  $\mathcal{V}_t$ , Proposition 3.1 applied with the mapping  $\pi_v$  indicates that a good candidate for the precision on  $e_v$  is  $\pi_v(H_t)$ , that is  $p^N \mathbb{Z}_p$ .

*About correctness.* We emphasize that the absolute precision computed this way is *not* proved, either for `ZpLF` or `ZpLC`. However, in the case of `ZpLC`, one can be slightly more precise. Let  $\mathcal{U}_t$  be the vector space of user-defined variables before time  $t$  and  $U_t$  be the lattice modeling the precision on them. The pair  $(\mathcal{U}_t, U_t)$  is defined inductively as follows: we set  $\mathcal{U}_0 = U_0 = 0$  and  $\mathcal{U}_{t+1} = \mathcal{U}_t \oplus \mathbb{Q}_p e_w$ ,  $U_{t+1} = U_t \oplus p^{\text{prec}} \mathbb{Z}_p e_w$  when a new variable  $w$  is created by “ $w = R(\text{value}, \text{prec})$ ”; otherwise, we put  $\mathcal{U}_{t+1} = \mathcal{U}_t$  and  $U_{t+1} = U_t$ . Moreover the values entered by the user defines a vector (with integral coordinates)  $\underline{u}_t \in \mathcal{U}_t$ .

Similarly, in order to model the caps, we define a pair  $(\mathcal{K}_t, K_t)$  by the recurrence  $\mathcal{K}_{t+1} = \mathcal{K}_t \oplus \mathbb{Q}_p e_w$ ,  $K_{t+1} = K_t \oplus p^{N_{t+1}} \mathbb{Z}_p e_w$  each time a new variable  $w$  is created. Here, the exponent  $N_{t+1}$  is the

cap defined by Eq. (4). In case of deletion, we put  $\mathcal{K}_{t+1} = \mathcal{K}_t$  and  $K_{t+1} = K_t$ .

Taking the composition of all the functions  $\tilde{F}$  (cf Eq. (3)) from time 0 to  $t$ , we find that the execution of the session until time  $t$  is modeled by a mathematical function  $\Phi_t : \mathcal{U}_t \oplus \mathcal{K}_t \rightarrow E_t$ . From the design of `ZpLC`, we deduce further that there exists a vector  $\underline{k}_t \in K_t$  such that:

$$\Phi_t(\underline{u}_t \oplus \underline{k}_t) = \underline{x}_t \quad \text{and} \quad d\Phi_t(U_t \oplus K_t) = H_t$$

where the differential of  $\Phi_t$  is taken at the point  $\underline{u}_t \oplus \underline{k}_t$ . Set  $\Phi_{t,v} = \pi_v \circ \Phi_t$ ; it maps  $\underline{u}_t \oplus \underline{k}_t$  to the  $v$ -coordinate  $x_{t,v}$  of  $\underline{x}_t$  and satisfies  $d\Phi_{t,v}(U_t \oplus K_t) = \pi_v(H_t) = p^N \mathbb{Z}_p$  where  $N$  is the value returned by `precision_absolute`. Thus, as soon as the assumptions of Proposition 3.1 are fulfilled, we derive  $\Phi_{t,v}(\underline{u}_t + U_t) \oplus (\underline{k}_t + K_t) = x_{t,v} + p^N \mathbb{Z}_p$ . Noting that  $k_t \in K_t$ , we finally get:

$$\Phi_{t,v}(\underline{u}_t + U_t) \subset \Phi_{t,v}(\underline{u}_t + U_t) \oplus K_t = x_{t,v} + p^N \mathbb{Z}_p. \quad (6)$$

The latter inclusion means that the computed value  $x_{t,v}$  is accurate at precision  $O(p^N)$ , *i.e.* that the output absolute precision is correct.

Unfortunately, automatically checking the assumptions of Proposition 3.1 in full generality is not straightforward because it requires bounds on higher derivatives. For now, our package does not perform this inspection but we plan to include it in a forthcoming release, along the lines of [4, Proposition 3.12]. Meanwhile, the assumptions can be checked by hand using the results of [3, 4, 11].

**Remark 3.2.** Assuming that Proposition 3.1 applies, the absolute precision computed as above is optimal if and only if the inclusion of (6) is an equality. Applying again Proposition 3.1 with the restricted mapping  $\Phi_{t,v} : \mathcal{U}_t \rightarrow \mathbb{Q}_p$  and the lattice  $U_t$ , we find that this happens if and only if  $d\Phi_{t,v}(U_t) = p^N \mathbb{Z}_p$ .

Unfortunately, the latter condition cannot be checked on the matrix  $M_t$  (because of reductions). However it is possible (and easy) to check whether the weaker condition  $d\Phi_{t,v}(K_t) \subsetneq p^N \mathbb{Z}_p$ . This checking is achieved by the method `is_precision_capped` (provided by our package) which returns true if  $d\Phi_{t,v}(K_t) = p^N \mathbb{Z}_p$ . As a consequence, when this method answers `FALSE`, the absolute precision computed by the software is likely optimal.

**Precision on a subset of elements.** Our package implements the method `precision_lattice` through which we can have access to the joint precision on a set of variables: it outputs a matrix (in echelon form) whose rows generate a lattice representing the precision on the subset of given variables.

When the variables are “independent”, the precision lattice is split and the method `precision_lattice` outputs a diagonal matrix:

```
In: x = ZZ(987, 10); y = ZZ(21, 5)
In: # We first retrieve the precision object
L = ZZ.precision()
In: L.precision_lattice([x, y])
ZpLC: [1024  0]
      [  0  32]
```

However, after some computations, the precision matrix evolves and does not remain diagonal in general (though it is always triangular because it is displayed in row-echelon form):

```
In: u, v = x+y, x-y
    L.precision_lattice([u,v])
ZpLC: [ 32 2016]
      [ 0 2048]
```

The fact that the precision matrix is no longer diagonal indicates that some well-chosen linear combinations of  $u$  and  $v$  are known with more digits than  $u$  and  $v$  themselves. In this particular example, the sum  $u + v$  is known at precision  $O(2^{11})$  while the (optimal) precision on  $u$  and  $v$  separately is only  $O(2^5)$ .

```
In: u, v
ZpLC: (...10000, ...00110)
In: u + v
ZpLC: ...11110110110
```

*Diffused digits of precision.* The phenomenon observed above is formalized by the notion of diffused digits of precision introduced in [5]. We recall briefly its definition.

**Definition 3.3.** Let  $E$  be a  $\mathbb{Q}_p$ -vector space endowed with a distinguished basis  $(e_1, \dots, e_n)$  and write  $\pi_i : E \rightarrow \mathbb{Q}_p e_i$  for the projections. Let  $H \subset E$  be a lattice. The number of *diffused digits of precision* of  $H$  is the length of  $H_0/H$  where  $H_0 = \pi_1(H) \oplus \dots \oplus \pi_n(H)$ .

If  $H$  represents the actual precision on some object, then  $H_0$  is the smallest diagonal lattice containing  $H$ . It then corresponds to the maximal *coordinate-wise* precision we can reach on the set of  $n$  variables corresponding to the basis  $(e_1, \dots, e_n)$ .

The method `diffused_digits` computes the number of diffused digits of precision on a set of variables. Observe:

```
In: L.diffused_digits([x,y])
ZpLC: 0
In: L.diffused_digits([u,v])
ZpLC: 6
```

For the last example, we recall that the relevant precision lattice  $H$  is generated by the  $2 \times 2$  matrix:

$$\begin{pmatrix} 2^5 & 2016 \\ 0 & 2^{11} \end{pmatrix}.$$

The minimal diagonal suplattice  $H_0$  of  $H$  is generated by the scalar matrix  $2^5 \cdot I_2$  and contains  $H$  with index  $2^6$  in it. This is where the 6 digits of precision come from. There are easily visible here: the sum  $u + v$  is known with 11 digits, that is exactly 6 more digits than the summands  $u$  and  $v$ .

Diffused digits frequently arise in practice. In the context of the matrix multiplication example of §2.2, we get

```
In: L.diffused_digits(M.list())
ZpLC: 11
```

### 3.4 Complexity

We now discuss the cost of the above operations. In what follows, we shall count operations in  $\mathbb{Q}_p$ . Although  $\mathbb{Q}_p$  is an inexact field, our model of complexity makes sense because the size of the  $p$ -adic numbers we manipulate will all have roughly the same size: for `ZpLF`, it is the precision we use for floating point arithmetic while, for `ZpLC`, it is the absolute cap which was fixed at the beginning.

It is convenient to introduce a total order on  $\mathcal{V}_t$ : for  $v, w \in \mathcal{V}_t$ , we say that  $v <_t w$  if  $v$  was created before  $w$ . By construction, the columns of the matrix  $M_t$  are ordered with respect to  $<_t$ . We denote by  $r_t$  (resp.  $c_t$ ) the number of rows (resp. columns) of  $M_t$ .

| Dimension      | 2  | 5   | 10    | 20     | 50        |
|----------------|----|-----|-------|--------|-----------|
| <b>Total</b>   | 35 | 424 | 5 539 | 83 369 | 3 170 657 |
| <b>Simult.</b> | 17 | 65  | 225   | 845    | 5 101     |

Computation of characteristic polynomial

| Degree         | 2  | 5   | 10  | 20    | 50    | 100    |
|----------------|----|-----|-----|-------|-------|--------|
| <b>Total</b>   | 54 | 130 | 332 | 1 036 | 4 110 | 10 578 |
| <b>Simult.</b> | 18 | 31  | 56  | 106   | 256   | 507    |

Naive Euclidean algorithm

**Figure 1: Numbers of involved variables**

By construction  $r_t$  is also the cardinality of  $\mathcal{V}_t$ . We have  $c_t \leq r_t$  and the equality always holds in the `ZpLC` case.

For  $v \in \mathcal{V}_t$ , we define the *index* of  $v$ , denoted by  $\text{ind}_t(v)$  as the number of elements of  $\mathcal{V}_t$  which are not greater than  $v$ . If we sort the elements of  $\mathcal{V}_t$  by increasing order,  $v$  then appears in  $\text{ind}_t(v)$ -th position. We also define the *co-index* of  $v$  by  $\text{coind}_t(v) = r_t - \text{ind}_t(v)$ .

Similarly, for any variable  $v \in \mathcal{V}_t$ , we define the *height* (resp. the *co-height*) of  $v$  at time  $t$  as the number of pivot variables  $w$  such that  $w \leq_t v$  (resp.  $w >_t v$ ). We denote it by  $\text{hgt}_t(v)$  (resp. by  $\text{cohgt}_t(v)$ ). Clearly  $\text{hgt}_t(v) + \text{cohgt}_t(v) = c_t$ . The height of  $v$  is the height of the significant part of the column of  $M_t$  which corresponds to  $v$ . In the case of `ZpLC`, all variables are pivot variables and thus  $\text{hgt}_t(v) = \text{ind}_t(v)$  and  $\text{cohgt}_t(v) = \text{coind}_t(v)$  for all  $v$ .

**Creating a variable.** With the notations of §3.2, it is obvious that creating a new variable  $w$  requires:

$$O\left(\sum_{i=1}^n \text{hgt}_t(v_i)\right) \subset O(n c_t)$$

operations in  $\mathbb{Q}_p$ . Here, we recall that  $n$  is the arity of the operation defining  $w$ . In most cases it is 2; thus the above complexity reduces to  $O(c_t)$ .

In the `ZpLF` context,  $c_t$  counts the number of user-defined variables. It is then expected to be constant (roughly equal to the size of the input) while running a given algorithm.

On the contrary, in the `ZpLC` context,  $c_t$  counts the number of variables which are alive at time  $t$ . It is no longer expected to be constant but evolves continuously when the algorithm runs. The tables of Figure 1 show the total number of created variables (which reflects the complexity) together with the maximum number of variables alive at the same time (which reflects the memory usage) while executing two basic computations. The first one is the computation of the characteristic polynomial of a square matrix by the default algorithm used by `SAGEMATH` for  $p$ -adic fields (which is a division-free algorithm of quartic complexity) while the second one is the computation of the gcd of two polynomials using a naive Euclidean algorithm (of quadratic complexity). We can observe that, for both of them, the memory usage is roughly equal to the square root of the complexity.

**Deleting a variable.** The deletion of the variable  $w$  induces the deletion of the corresponding column of  $M_t$ , possibly followed

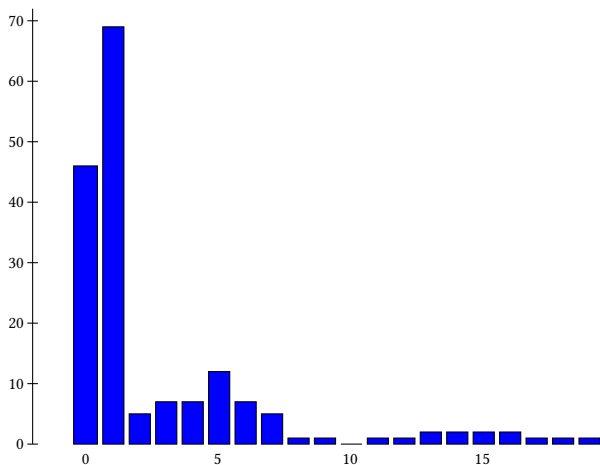


Figure 2: The distribution of  $\text{coind}_t(w)$

by a partial row-echelonization. In terms of algebraic complexity, the deletion is free. The cost of the echelonization is within  $O(\text{coind}_t(w) \cdot \text{cohgt}_t(w))$  operations in  $\mathbb{Q}_p$ .

In the **ZpLF** case, we expect that, most of the time, the deleted variables were created after all initial variables were set by the user. This means that we expect  $\text{cohgt}_t(w)$  to vanish and so, the corresponding cost to be negligible.

In the **ZpLC** case, we always have  $\text{cohgt}_t(w) = \text{coind}_t(w)$ , so that the cost becomes  $O(\text{coind}_t(w)^2)$ , which seems high *a priori*. However, the principle of temporal locality [8] asserts that  $\text{coind}_t(w)$  tends to be small: destroyed variables are often recently created ones. As a simple example, variables which are local to a small piece of code (e.g. a short function or a loop) have a short lifetime. The histogram of Figure 2 shows the distribution of  $\text{coind}_t(w)$  while executing the Euclidean algorithm (naive implementation) with two polynomials of degree 7 as input. The bias is evident: most of the time  $\text{coind}_t(w) \leq 1$ .

**Summary: Impact on complexity.** We consider the case of an algorithm with the following characteristics: its complexity is  $c$  operations in  $\mathbb{Q}_p$  (without any tracking of precision), its memory usage is  $m$  elements of  $\mathbb{Q}_p$ , its input and output have size  $s_{\text{in}}$  and  $s_{\text{out}}$  (elements of  $\mathbb{Q}_p$ ) respectively.

In the case of **ZpLF**, creating a variable has a cost  $O(s_{\text{in}})$  whereas deleting a variable is free. Thus when executed with the **ZpLF** mechanism, the complexity of our algorithm becomes  $O(s_{\text{in}}c)$ .

In the **ZpLC** framework, creating a variable has a cost  $O(m)$ . The case of deletion is more difficult to handle. However, by the temporal locality principle, it seems safe to assume that it is not the bottleneck (which is the case in practice). Therefore, when executed with the **ZpLF** mechanism, the cost of our algorithm is expected to be roughly  $O(mc)$ . Going further in speculation, we might estimate the magnitude of  $m$  as about  $s + \sqrt{c}$  with  $s = \max(s_{\text{in}}, s_{\text{out}})$ , leading to a complexity of  $O(c^{3/2} + sc)$ . For quasi-optimal algorithms, the term  $sc \approx c^2$  dominates. However, as soon as the complexity is at least quadratic in  $s$ , the dominant term is  $c^{3/2}$  and the impact on the complexity is then limited.

## 4 CONCLUSION

The package **ZpL** provides powerful tools (based on automatic differentiation) to track precision in the  $p$ -adic setting. It frequently outperforms standard interval arithmetic in terms of the precision of the output, as shown in §2. The impact on complexity is controlled but nevertheless non-negligible (see §3.4). For this reason, it is unlikely that a fast algorithm will rely *directly* on the machinery proposed by **ZpL**, though it might do so for a specific part of a computation. At least for now, bringing together rapidity and stability still requires a substantial human contribution and a careful study of all parameters.

Nevertheless, we believe that **ZpL** can be extremely helpful to anyone designing a fast and stable  $p$ -adic algorithm for a couple of reasons. First, it provides mechanisms to automatically detect which steps of a given algorithm are stable and which ones are not. In this way, it highlights the parts of the algorithm on which the researcher has to concentrate their effort. Second, recall that a classical strategy to improve stability consists of working internally at higher precision. Finding the internal increase in precision that best balances efficiency and accuracy is not an easy task in general. Understanding the diffused precision gives very useful hints in this direction. For example, when there are no diffused digits of precision then the optimal precision completely splits over the variables and there is no need to internally increase the precision. On the contrary, when there are many diffused digits of precision, a large increment is required. Since **ZpL** gives a direct access to the number of diffused digits of precision, it can be very useful to the designer who is concerned with the balance between efficiency and accuracy.

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