

# SYMPY: SYMBOLIC COMPUTING IN PYTHON

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**1. Introduction.** SymPy is a full featured computer algebra system (CAS) written in the Python programming language. It is open source, being licensed under the extremely permissive 3-clause BSD license. SymPy was started by Ondřej Čertík in 2005, and it has since grown into a large open source project, with over 500 contributors. SymPy is developed on GitHub using a bazaar community model [38]. The accessibility of the codebase and the open community model allows SymPy to rapidly respond to the needs of the community of users, and has made the large contributor count possible.

SymPy is written entirely in the Python programming language. Python is a popular dynamically typed programming language that has a focus on ease of use and readability. It also a very popular language for scientific computing and data science, with a wide range of useful libraries [33]. SymPy is itself used by many libraries and tools across many domains, such as Sage [42] (pure mathematics), yt [45] (astronomy and astrophysics), PyDi (multibody dynamics), and SfePy [16] (finite elements).

Unlike many CASs, SymPy does not invent its own programming language. Python is used both for the internal implementation and the user interaction. Exclusively using Python in this way makes it easier for people already familiar with the language to use or develop SymPy. It also lets the SymPy developers focus on mathematics, rather than language design.

SymPy is designed with a strong focus that it be usable as a library. This means that extensibility is important in its application program interface (API) design. This is also one of the reasons SymPy makes no attempt to extend the Python language itself. The goal is for users of SymPy to be able to import SymPy alongside other Python libraries in their workflow, whether that is an interactive workflow or programmatic use as part of a larger system.

Being developed as a library, SymPy does not have a built-in graphical user interface (GUI). However, SymPy exposes a rich interactive display system, including registering printers with Jupyter [35] frontends, including the Notebook and Qt Console, which will pretty print SymPy expressions using MathJax or L<sup>A</sup>T<sub>E</sub>X rendering.

Section 2 discusses the architecture of SymPy. Following that, Section 3 looks at the numerical features of SymPy and its dependency library, mpmath. Section 4 enumerates the features of SymPy and takes a closer look at some of the important ones. Section 5 looks at the domain specific physics submodules for doing classical mechanics and quantum mechanics. Finally, Section 6 concludes the paper and discusses future work.

## 2. Architecture.

**2.1. Basic Usage.** Being built on Python, SymPy requires that all variable names be defined before they can be used. The statement

```
>>> from sympy import *
```

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will import all SymPy functions into the global Python namespace. All the examples in this paper assume that this has been run.

The symbolic nature of SymPy comes from its implementation of symbolic variables, called symbols, which must be defined and assigned to Python variables before they can be used. This is typically done through the `symbols` function, which creates multiple symbols at once. For instance,

```
>>> x, y, z = symbols('x y z')
```

creates three symbols representing variables named  $x$ ,  $y$ , and  $z$ , assigned to Python variables of the same name. The Python variable names that symbols are assigned to are immaterial—we could have just as well have written `a, b, c = symbol('x y z')`. All the examples in this paper will assume that the symbols  $x$ ,  $y$ , and  $z$  have been assigned as above.

Expressions are created from symbols using Python syntax, which mirrors usual mathematical notation. Note that in Python, exponentiation is `**`, as:

```
>>> (x**2 - 2*x + 3)/y
(x**2 - 2*x + 3)/y
```

All SymPy expressions are immutable. This simplifies the design by allowing interning. It also allows expressions to be hashed and stored in a Python dictionary, which enables caching and other features.

**2.2. The Core.** The core of a computer algebra system (CAS) refers to the module that is in charge of resending symbolic expressions and performing basic manipulations with them. In SymPy, every symbolic expression is an instance of a Python class. Expressions are represented by expression trees. The operators are represented by the type of an expression and the child nodes are stored in the `args` attribute. A leaf node in the expression tree has an empty `args`. The `args` attribute is provided by the class `Basic`, which is a superclass of all SymPy objects and provides common methods to all SymPy tree-elements. For example, consider the expression  $xy + 2$ :

```
>>> expr = x*y + 2
```

By order of operations, the parent of the expression tree for `expr` is an addition, so it is of type `Add`. The child nodes of `expr` are 2 and  $x*y$ .

```
>>> type(expr)
<class 'sympy.core.add.Add'>
>>> expr.args
(2, x*y)
```

We can dig further into the expression tree to see the full expression. For example, the first child node, given by `expr.args[0]` is 2. Its class is `Integer`, and it has empty `args`, indicating that it is a leaf node.

```
>>> expr.args[0]
2
>>> type(expr.args[0])
<class 'sympy.core.numbers.Integer'>
>>> expr.args[0].args
()
```

The function `srepr` returns a string representation of the object as valid Python code, which contains all the nested class constructor calls to create the given expression.

```
>>> srepr(expr)
"Add(Mul(Symbol('x'), Symbol('y')), Integer(2))"
```

Every SymPy expression satisfies a key invariant, namely, `expr.func(*expr.args) == expr`.<sup>1</sup> This means that expressions are rebuildable from their `args`. Here, we note that in SymPy, the `==` operator represents exact structural equality, not just mathematical equality. This allows one to test if any two expressions are equal to one another as expression trees.

Python allows classes to override mathematical operators. The Python interpreter translates the above `x*y + 2` to, roughly, `(x.__mul__(y)).__add__(2)`. Both `x` and `y`, returned from the `symbols` function, are `Symbol` instances. The `2` in the expression is processed by Python as a literal, and is stored as Python's builtin `int` type. When `2` is called by the `__add__` method of `Symbol`, it is converted to the SymPy type `Integer(2)`. In this way, SymPy expressions can be built in the natural way using Python operators and numeric literals.

One must be careful in one particular instance. Python does not have a builtin rational literal type. Given a fraction of integers such as `1/2`, Python will perform floating point division and produce `0.5`.<sup>2</sup> Python uses eager evaluation, so expressions like `x + 1/2` will produce `x + 0.5`, and by the time any SymPy function sees the `1/2` it has already been converted to `0.5` by Python. However, for a CAS like SymPy, one typically wants to work with exact rational numbers whenever possible. Working around this is simple, however: one can wrap one of the integers with `Integer`, like `x + Integer(1)/2`, or using `x + Rational(1, 2)`. SymPy provides a function `S` which can be used to convert objects to SymPy types with minimal typing, such as `x + S(1)/2`. This gotcha is a small downside to using Python directly instead of a custom domain specific language (DSL), and we consider it to be worth it for the advantages listed above.

**2.3. Assumptions.** An important feature of the SymPy core is the assumptions system. The assumptions system allows users to specify that symbols have certain common mathematical properties, such as being positive, imaginary, or integer. SymPy is careful to never perform simplifications on an expression unless the assumptions allow them. For instance, the identity  $\sqrt{x^2} = x$  holds if  $x$  is nonnegative ( $x \geq 0$ ). If  $x$  is real, the identity  $\sqrt{x^2} = |x|$  holds. However, for general complex  $x$ , no such identity holds.

By default, SymPy performs all calculations assuming that variables are complex valued. This assumption makes it easier to treat mathematical problems in full generality.

```
>>> t = Symbol('t')
>>> sqrt(t**2)
sqrt(t**2)
```

By assuming the most general case, that symbols are complex by default, SymPy avoids performing mathematically invalid operations. However, in many cases users will wish to simplify expressions containing terms like  $\sqrt{t^2}$ .

Assumptions are set on `Symbol` objects when they are created. For instance `Symbol('t', positive=True)` will create a symbol named `x` that is assumed to be positive.

```
>>> t = Symbol('t', positive=True)
>>> sqrt(t**2)
```

<sup>1</sup>`expr.func` is used instead of `type(expr)` to allow the function of an expression to be distinct from its actual Python class. In most cases the two are the same.

<sup>2</sup>This is the behavior in Python 3. In Python 2, `1/2` will perform integer division and produce `0`, unless one uses `from __future__ import division`.

`t`  
 Some common assumptions that SymPy allows are `positive`, `negative`, `real`, `nonpositive`,  
`nonnegative`, `real`, `integer`, and `commutative`<sup>3</sup>. Assumptions on any object can be  
 checked with the `is_assumption` attributes, like `t.is_positive`.

Assumptions are only needed to restrict a domain so that certain simplifications  
 can be performed. It is not required to make the domain match the input of a function.  
 For instance, one can create the object  $\sum_{n=0}^m f(n)$  as `Sum(f(n), (n, 0, m))` without  
 setting `integer=True` when creating the Symbol object `n`.

The assumptions system additionally has deductive capabilities. The assump-  
 tions use a three-valued logic using the Python builtin objects `True`, `False`, and  
`None`. `None` represents the “unknown” case. This could mean that the given as-  
 sumption could be either true or false under the given information, for instance,  
`Symbol('x', real=True).is_positive` will give `None` because a real symbol might be  
 positive or it might not. It could also mean not enough is implemented to compute  
 the given fact, for instance, `(pi + E).is_irrational` gives `None`, because SymPy does  
 not know how to determine if  $\pi + e$  is rational or irrational, indeed, it is an open  
 problem in mathematics.

Basic implications between the facts are used to deduce assumptions. For in-  
 stance, the assumptions system knows that being an integer implies being ratio-  
 nal, so `Symbol('x', integer=True).is_rational` returns `True`. Furthermore, expres-  
 sions compute the assumptions on themselves based on the assumptions of their  
 arguments. For instance, if `x` and `y` are both created with `positive=True`, then  
`(x + y).is_positive` will be `True`.

SymPy also has an experimental assumptions system where facts are stored sep-  
 arate from objects, and deductions are made with a SAT solver. We will not discuss  
 this system here.

**2.4. Extensibility.** Extensibility is an important feature for SymPy. Because  
 the same language, Python, is used both for the internal implementation and the  
 external usage by users, all the extensibility capabilities available to users are also  
 used by functions that are part of SymPy.

The typical way to create a custom SymPy object is to subclass an existing SymPy  
 class, generally either `Basic`, `Expr`, or `Function`. All SymPy classes used for expression  
 trees<sup>4</sup> should be subclasses of the base class `Basic`, which defines some basic methods  
 for symbolic expression trees. `Expr` is the subclass for mathematical expressions that  
 can be added and multiplied together. Instances of `Expr` typically represent complex  
 numbers, but may also include other “rings” like matrix expressions. Not all SymPy  
 classes are subclasses of `Expr`. For instance, logic expressions, such as `And(x, y)` are  
 subclasses of `Basic` but not of `Expr`.

The `Function` class is a subclass of `Expr` which makes it easier to define mathe-  
 matical functions called with arguments. This includes named functions like  $\sin(x)$   
 and  $\log(x)$  as well as undefined functions like  $f(x)$ . Subclasses of `Function` should  
 define a class method `eval`, which returns values for which the function should be  
 automatically evaluated, and `None` for arguments that should not be automatically  
 evaluated.

Many SymPy functions require various evaluations down the expression tree. The

<sup>3</sup>If  $A$  and  $B$  are Symbols created with `commutative=False` then SymPy will keep  $A \cdot B$  and  $B \cdot A$  distinct.

<sup>4</sup>Some internal classes, such as those used in the polynomial module, do not follow this rule for efficiency reasons.

evaluation of such functions on of classes in SymPy is performed by defining a relevant `_eval_*` method on the class. For instance, an object can signal to SymPy's `diff` function how to take the derivative of itself by defining the `_eval_derivative(self, x)` method, which may in turn call `diff` on its args. The most common `_eval_*` methods relate to the assumptions. `_eval_is_assumption` defines the assumptions for *assumption*.

As an example of the notions presented in this section, we present below a stripped down version of the gamma function  $\Gamma(x)$  from SymPy, which evaluates itself on positive integer arguments, has the positive and real assumptions defined, can be rewritten in terms of factorial with `gamma(x).rewrite(factorial)`, and can be differentiated. `fdiff` is a convenience method for subclasses of `Function`. `fdiff` returns the derivative of the function without worrying about the chain rule. `self.func` is used throughout instead of referencing `gamma` explicitly so that potential subclasses of `gamma` can reuse the methods.

```
from sympy import Integer, Function, floor, factorial, polygamma
```

```
class gamma(Function)
    @classmethod
    def eval(cls, arg):
        if isinstance(arg, Integer) and arg.is_positive:
            return factorial(arg - 1)

    def _eval_is_real(self):
        x = self.args[0]
        # noninteger means real and not integer
        if x.is_positive or x.is_noninteger:
            return True

    def _eval_is_positive(self):
        x = self.args[0]
        if x.is_positive:
            return True
        elif x.is_noninteger:
            return floor(x).is_even

    def _eval_rewrite_as_factorial(self, z):
        return factorial(z - 1)

    def fdiff(self, argindex=1):
        from sympy.core.function import ArgumentIndexError
        if argindex == 1:
            return self.func(self.args[0])*polygamma(0, self.args[0])
        else:
            raise ArgumentIndexError(self, argindex)
```

The actual gamma function defined in SymPy has many more capabilities, such as evaluation at rational points and series expansion.

**3. Numerics.** The `Float` class holds an arbitrary-precision binary floating-point value and a precision in bits. An operation between two `Float` inputs is rounded to the larger of the two precisions. Since Python floating-point literals automatically

230 evaluate to `double` (53-bit) precision, strings should be used to input precise decimal  
231 values:

```
232 >>> Float(1.1)
233 1.1000000000000000
234 >>> Float(1.1, 30) # precision equivalent to 30 digits
235 1.100000000000000008881784197001
236 >>> Float("1.1", 30)
237 1.1000000000000000000000000000000000
```

238 The preferred way to evaluate an expression numerically is with the `evalf` method,  
239 which internally estimates the number of accurate bits of the floating-point approxi-  
240 mation for each sub-expression, and adaptively increases the working precision until  
241 the estimated accuracy of the final result matches the sought number of decimal digits.

242 The internal error tracking does not provide rigorous error bounds (in the sense  
243 of interval arithmetic) and cannot be used to track uncertainty in measurement data  
244 in any meaningful way; the sole purpose is to mitigate loss of accuracy that typically  
245 occurs when converting symbolic expressions to numerical values, for example due to  
246 catastrophic cancellation. This is illustrated by the following example (the input 25  
247 specifies that 25 digits are sought):

```
248 >>> cos(exp(-100)).evalf(25) - 1
249 0
250 >>> (cos(exp(-100)) - 1).evalf(25)
251 -6.919482633683687653243407e-88
```

252 The `evalf` method works with complex numbers and supports more complicated  
253 expressions, such as special functions, infinite series and integrals.

254 SymPy does not track the accuracy of approximate numbers outside of `evalf`.  
255 The familiar dangers of floating-point arithmetic apply [22], and symbolic expres-  
256 sions containing floating-point numbers should be treated with some caution. This  
257 approach is similar to Maple and Maxima.

258 By contrast, Mathematica uses a form of significance arithmetic [40] for approx-  
259 imate numbers. This offers further protection against numerical errors, but leads to  
260 non-obvious semantics while still not being mathematically rigorous (for a critique of  
261 significance arithmetic, see Fateman [17]). SymPy's `evalf` internals are non-rigorous  
262 in the same sense, but have no bearing on the semantics of floating-point numbers in  
263 the rest of the system.

264 **3.1. The mpmath library.** The implementation of arbitrary-precision floating-  
265 point arithmetic is supplied by the `mpmath` library, which originally was developed  
266 as a SymPy module but subsequently has been moved to a standalone pure Python  
267 package. The basic datatypes in `mpmath` are `mpf` and `mpc`, which respectively act  
268 as multiprecision substitutes for Python's `float` and `complex`. The floating-point  
269 precision is controlled by a global context:

```
270 >>> import mpmath
271 >>> mpmath.mp.dps = 30 # 30 digits of precision
272 >>> mpmath.mpf("0.1") + mpmath.exp(-50)
273 mpf('0.10000000000000000000000000000000000192874984794')
274 >>> print(_) # pretty-printed
275 0.10000000000000000000000000000000000192874985
```

276 For pure numerical computing, it is convenient to use `mpmath` directly with `from`  
277 `mpmath import *` (it is best to avoid such an import statement when using SymPy  
278 simultaneously, since numerical functions such as `exp` will shadow the symbolic coun-

terparts in SymPy).

Like SymPy, mpmath is a pure Python library. Internally, mpmath represents a floating-point number  $(-1)^s x \cdot 2^y$  by a tuple  $(s, x, y, b)$  where  $x$  and  $y$  are arbitrary-size Python integers and the redundant integer  $b$  stores the bit length of  $x$  for quick access. If GMPY [25] is installed, mpmath automatically switches to using the `gmpy.mpz` type for  $x$  and using GMPY helper methods to perform rounding-related operations, improving performance.

The mpmath library includes support for special functions, root-finding, linear algebra, polynomial approximation, and numerical computation of limits, derivatives, integrals, infinite series, and ODE solutions. All features work in arbitrary precision and use algorithms that support computing hundreds of digits rapidly, except in degenerate cases.

The double exponential (tanh-sinh) quadrature is used for numerical integration by default. For smooth integrands, this algorithm usually converges extremely rapidly, even when the integration interval is infinite or singularities are present at the endpoints [43, 9]. However, for good performance, singularities in the middle of the interval must be specified by the user. To evaluate slowly converging limits and infinite series, mpmath automatically attempts to apply Richardson extrapolation and the Shanks transformation (Euler-Maclaurin summation can also be used) [10]. A function to evaluate oscillatory integrals by means of convergence acceleration is also available.

A wide array of higher mathematical functions are implemented with full support for complex values of all parameters and arguments, including complete and incomplete gamma functions, Bessel functions, orthogonal polynomials, elliptic functions and integrals, zeta and polylogarithm functions, the generalized hypergeometric function, and the Meijer G-function.

Most special functions are implemented as linear combinations of the generalized hypergeometric function  ${}_pF_q$ , which is computed by a combination of direct summation, argument transformations (for  ${}_2F_1$ ,  ${}_3F_2$ , ...) and asymptotic expansions (for  ${}_0F_1$ ,  ${}_1F_1$ ,  ${}_1F_2$ ,  ${}_2F_2$ ,  ${}_2F_3$ ) to cover the whole complex domain. Numerical integration and generic convergence acceleration are also used in a few special cases.

In general, linear combinations and argument transformations give rise to singularities that have to be removed for certain combinations of parameters. A typical example is the modified Bessel function of the second kind

$$K_\nu(z) = \frac{1}{2} \left[ \left(\frac{z}{2}\right)^{-\nu} \Gamma(\nu) {}_0F_1\left(1 - \nu, \frac{z^2}{4}\right) - \left(\frac{z}{2}\right)^\nu \frac{\pi}{\nu \sin(\pi\nu) \Gamma(\nu)} {}_0F_1\left(\nu + 1, \frac{z^2}{4}\right) \right]$$

where the limiting value  $\lim_{\varepsilon \rightarrow 0} K_{n+\varepsilon}(z)$  has to be computed when  $\nu = n$  is an integer. A generic algorithm is used to evaluate hypergeometric-type linear combinations of the above type. This algorithm automatically detects cancellation problems, and computes limits numerically by perturbing parameters whenever internal singularities occur (the perturbation size is automatically decreased until the result is detected to converge numerically).

Due to this generic approach, particular combinations of hypergeometric functions can be specified easily. The implementation of the Meijer G-function takes only a few dozen lines of code, yet covers the whole input domain in a robust way. The Meijer G-function instance  $G_{1,3}^{3,0}(0; \frac{1}{2}, -1, -\frac{3}{2}|x)$  is a good test case [44]; past versions of both Maple and Mathematica produced incorrect numerical values for large  $x > 0$ . Here, mpmath automatically removes the internal singularity and compensates for

325 cancellations (amounting to 656 bits of precision when  $x = 10000$ ), giving correct  
326 values:

```
327 >>> mpmath.mp.dps = 15
328 >>> mpmath.meijerg([], [0], [[-0.5, -1, -1.5], []], 10000)
329 2.4392576907199564e-94
```

330 Equivalently, with SymPy's interface this function can be evaluated as:

```
331 >>> meijerg([], [0], [-S(1)/2, -1, -S(3)/2], [], 10000).evalf()
332 2.43925769071996e-94
```

333 We highlight the generalized hypergeometric functions and the Meijer G-function,  
334 due to those functions' frequent appearance in closed forms for integrals and sums (see  
335 Section 4.2). Via mpmath, SymPy has relatively good support for evaluating sums  
336 and integrals numerically, using two complementary approaches: direct numerical  
337 evaluation, or first computing a symbolic closed form involving special functions.

338 **3.2. Numerical simplification.** The `nsimplify` function in SymPy (a wrapper  
339 of `identify` in mpmath) attempts to find a simple symbolic expression that evaluates  
340 to the same numerical value as the given input. It works by applying a few simple  
341 transformations (including square roots, reciprocals, logarithms and exponentials) to  
342 the input and, for each transformed value, using the PSLQ algorithm [18] to search  
343 for a matching algebraic number or optionally a linear combination of user-provided  
344 base constants (such as  $\pi$ ).

```
345 >>> t = 1 / (sin(pi/5)+sin(2*pi/5)+sin(3*pi/5)+sin(4*pi/5))*2
346 >>> nsimplify(t)
347 -2*sqrt(5)/5 + 1
348 >>> nsimplify(pi, tolerance=0.01)
349 22/7
350 >>> nsimplify(1.783919626661888, [pi], tolerance=1e-12)
351 pi/(-1/3 + 2*pi/3)
```

352 **4. Features.** SymPy has an extensive feature set that encompasses too much  
353 to cover in-depth here. Bedrock areas, such as calculus, receive their own subsections  
354 below. Table 1 gives a compact listing of all major capabilities present in the  
355 SymPy codebase. This gives a sampling from the breadth of topics and application  
356 domains that SymPy services. Unless stated otherwise, all features noted in Table 1  
357 are symbolic in nature. Numeric features are discussed in Section 3.

Table 1: SymPy Features and Descriptions

Feature	Description
Calculus	Algorithms for computing derivatives, integrals, and limits.
Category Theory	Representation of objects, morphisms, and diagrams. Tools for drawing diagrams with Xy-pic.
Code Generation	Enables generation of compilable and executable code in a variety of different programming languages directly from expressions. Target languages include C, Fortran, Julia, JavaScript, Mathematica, Matlab and Octave, Python, and Theano.



Combinatorics Group Theory	&	Implements permutations, combinations, partitions, subsets, various permutation groups (such as polyhedral, Rubik, symmetric, and others), Gray codes [32], and Prufer sequences [11].
Concrete Math		Summation, products, tools for determining whether summation and product expressions are convergent, absolutely convergent, hypergeometric, and other properties. May also compute Gosper's normal form [37] for two univariate polynomials.
Cryptography		Represents block and stream ciphers, including shift, Affine, substitution, Vigenere's, Hill's, bifid, RSA, Kid RSA, linear-feedback shift registers, and Elgamal encryption
Differential Geome- try Geometry		Classes to represent manifolds, metrics, tensor products, and coordinate systems. Allows the creation of 2D geometrical entities, such as lines and circles. Enables queries on these entities, such as asking the area of an ellipse, checking for collinearity of a set of points, or finding the intersection between two lines.
Lie Algebras Logic		Represents Lie algebras and root systems. boolean expression, equivalence testing, satisfiability, normal forms.
Matrices		Tools for creating matrices of symbols and expressions. This is capable of both sparse and dense representations and performing symbolic linear algebraic operations (e.g., inversion and factorization).
Matrix Expressions		Matrices with symbolic dimensions (unspecified entries). Block matrices.
Number Theory		prime number generation, primality testing, integer factorization, continued fractions, Egyptian fractions, modular arithmetic, quadratic residues, partitions, binomial and multinomial coefficients, prime number tools, integer factorization.
Plotting		Hooks for visualizing expressions via matplotlib [?] or as text drawings when lacking a graphical back-end. 2D function plotting, 3D function plotting, and 2D implicit function plotting are supported.
Polynomials		Computes polynomial algebras over various coefficient domains. Functionality ranges from the simple (e.g., polynomial division) to the advanced (e.g., Gröbner bases [8] and multivariate factorization over algebraic number domains).
Printing		Functions for printing SymPy expressions in the terminal with ASCII or Unicode characters, and converting SymPy expressions to L <sup>A</sup> T <sub>E</sub> X and MathML.
Series		Implements series expansion, sequences, and limit of sequences. This includes Taylor, Laurent and Puiseux series as well as special series, such as Fourier and formal power series.

Sets	Representations of empty, finite, and infinite sets. This includes special sets such as for all natural, integer, and complex numbers. Operations on sets such as union, intersection, Cartesian product, and building sets from other sets.
Simplification	Functions for manipulating and simplifying expressions. Includes algorithms for simplifying hypergeometric functions, trigonometric expressions, rational functions, combinatorial functions, square root denesting, and common subexpression elimination.
Solvers	Functions for symbolically solving equations algebraically, systems of equations, both linear and non-linear, inequalities, ordinary differential equations, partial differential equations, Diophantine equations, and recurrence relations.
Special Functions	Implements a number of well known special functions, including Dirac delta, Gamma, Beta, Gauss error functions, Fresnel integrals, Exponential integrals, Logarithmic integrals, Trigonometric integrals, Bessel, Hankel, Airy, B-spline, Riemann Zeta, Dirichlet eta, polylogarithm, Lerch transcendent, hypergeometric, elliptic integrals, Mathieu, Jacobi polynomials, Gegenbauer polynomial, Chebyshev polynomial, Legendre polynomial, Hermite polynomial, Laguerre polynomial, and spherical harmonic functions.
Statistics	Support for a random variable type as well as the ability to declare this variable from prebuilt distribution functions such as Normal, Exponential, Coin, Die, and other custom distributions.
Tensors	Symbolic manipulation of indexed objects.
Vectors	Provides basic vector math and differential calculus with respect to 3D Cartesian coordinate systems.

**4.1. Simplification.** The generic way to simplify an expression is by calling the `simplify` function. It must be emphasized that simplification is not an unambiguously defined mathematical operation [15]. The `simplify` function applies several simplification routines along with some heuristics to make the output expression as “simple” as possible.

It is often preferable to apply more directed simplification functions. These apply very specific rules to the input expression, and are often able to make guarantees about the output (for instance, the `factor` function, given a polynomial with rational coefficients in several variables, is guaranteed to produce a factorization into irreducible factors). Table 2 lists some common simplification functions.

Table 2: SymPy Simplification Functions

<code>expand</code>	expand the expression
<code>factor</code>	factor a polynomial into irreducibles
<code>collect</code>	collect polynomial coefficients
<code>cancel</code>	rewrite a rational function as $p/q$ with common factors canceled

<code>apart</code>	compute the partial fraction decomposition of a rational function
<code>trigsimp</code>	simplify trigonometric expressions [20]

---

Substitutions are performed through the `.subs` method, which is sensible to some mathematical properties while matching, such as associativity, commutativity, additive and multiplicative inverses, and matching of powers.

**4.2. Calculus.** Derivatives can be computed with the `diff` function.

```
>>> diff(sin(x), x)
```

```
cos(x)
```

Unevaluated `Derivative` objects are also supported.

```
>>> expr = Derivative(sin(x), x)
```

```
>>> expr
```

```
Derivative(sin(x), x)
```

Unevaluated expressions can be evaluated with the `doit` method.

```
>>> expr.doit()
```

```
cos(x)
```

Integrals can be analogously, calculated either with the `integrate` function, or the unevaluated `Integral` objects.

```
>>> integrate(sin(x), x)
```

```
-cos(x)
```

```
>>> expr = Integral(sin(x), x)
```

```
>>> expr
```

```
Integral(sin(x), x)
```

```
>>> expr.doit()
```

```
-cos(x)
```

Definite integration can be calculated with the same method, by specifying a range of the integration variable. The following computes  $\int_0^1 \sin(x) dx$ .

```
>>> integrate(sin(x), (x, 0, 1))
```

```
-cos(1) + 1
```

SymPy implements a combination of the Risch algorithm [14], table lookups, a reimplement of Manuel Bronstein’s “Poor Man’s Integrator” [13], and an algorithm for computing integrals based on Meijer G-functions. These allow SymPy to compute a wide variety of indefinite and definite integrals.

Summations and products are also supported, via the evaluated `summation` and `product` and unevaluated `Sum` and `Product`, and use the same syntax as `integrate`. Summations are computed using a combination of Gosper’s algorithm and an algorithm that uses Meijer G-functions. Products are computed via some heuristics.

The limit module implements the Gruntz algorithm [23] for computing symbolic limits. For example, the following computes  $\lim_{x \rightarrow \infty} x \sin(\frac{1}{x}) = 1$  (note that  $\infty$  is `oo` in

SymPy).

```
>>> limit(x*sin(1/x), x, oo)
```

```
1
```

As a more complicated example, SymPy computes  $\lim_{x \rightarrow 0} \left( 2e^{\frac{1-\cos(x)}{\sin(x)}} - 1 \right)^{\frac{\sinh(x)}{\operatorname{atan}^2(x)}} = e$ .

```
>>> limit((2*E**((1-cos(x))/sin(x))-1)**(sinh(x)/atan(x)**2), x, 0)
```

```
E
```

**4.3. Printers.** SymPy has a rich collection of expression printers for displaying expressions to the user. By default, an interactive Python session will render the `str` form of an expression, which has been used in all the examples in this paper so far.

```

413 >>> phi0 = Symbol('phi0')
414 >>> str(Integral(sqrt(phi0), phi0))
415 'Integral(sqrt(phi0), phi0)'
416 Expressions can be printed with 2D monospace text with pprint. This uses
417 Unicode characters to render mathematical symbols such as integral signs, square
418 roots, and parentheses. Greek letters and subscripts in symbol names are rendered
419 automatically.
420 >>> pprint(Integral(sqrt(phi0 + 1), phi0))
    ∫ √ φ₀ + 1 d(φ₀)
421 Alternately, the use_unicode=False flag can be set, which causes the expression to be
422 printed using only ASCII characters.
423 >>> pprint(Integral(sqrt(phi0 + 1), phi0), use_unicode=False)
424 /
425 |
426 | _____
427 | \ / phi0 + 1 d(phi0)
428 |
429 /
430 The function latex returns a LATEX representation of an expression.
431 >>> print(latex(Integral(sqrt(phi0 + 1), phi0)))
432 \int \sqrt{\phi_0 + 1}\, d\phi_0
433 Users are encouraged to run the init_printing function at the beginning of in-
434 teractive sessions, which automatically enables the best pretty printing supported by
435 their environment. In the Jupyter notebook or qtconsole [35] the LATEX printer is
436 used to render expressions using MathJax or LATEX if it is installed on the system.
437 The 2D text representation is used otherwise.
438 Other printers such as MathML are also available. SymPy uses an extensible
439 printer subsystem which allows users to customize the printing for any given printer,
440 and for custom objects to define their printing behavior for any printer. SymPy's
441 code generation capabilities, which we will not discuss in-depth here, use the same
442 printer model.
443 4.4. Solvers. SymPy has a module of equation solvers for symbolic equations.
444 There are two submodules to solve algebraic equations in SymPy, referred to as old
445 solve function, solve, and new solve function, solveset. Solveset is introduced with
446 several design changes with respect to the old solve function to resolve the issues
447 with old solve function, for example old solve function's input API has many flags
448 which are not needed and they make it hard for the user and the developers to work
449 on solvers. In contrast to the old solve function, the solveset has a clean input API,
450 it only asks for the necessary information from the user. The function signatures of
451 the old and new solve function:
452 solve(f, *symbols, **flags) # old solve function
453 solveset(f, symbol, domain) # new solve function
454 The old solve function has an inconsistent output API for various types of inputs,
455 whereas the solveset has a canonical output API which is achieved using sets. It can
456 consistently return various types of solutions.
457 • Single solution
458 >>> solveset(x - 1)

```

```

459 {1}
460     • Finite set of solution, quadratic equation
461 >>> solveset(x**2 - pi**2, x)
462 {-pi, pi}
463     • No Solution
464 >>> solveset(1, x)
465 EmptySet()
466     • Interval of solution
467 >>> solveset(x**2 - 3 > 0, x, domain=S.Reals)
468 (-oo, -sqrt(3)) U (sqrt(3), oo)
469     • Infinitely many solutions
470 >>> solveset(sin(x) - 1, x, domain=S.Reals)
471 ImageSet(Lambda(_n, 2*_n*pi + pi/2), Integers())
472 >>> solveset(x - x, x, domain=S.Reals)
473 (-oo, oo)
474 >>> solveset(x - x, x, domain=S.Complexes)
475 S.Complexes
476     • Linear system: finite and infinite solution for determined, under determined
477       and over determined problems.
478 >>> A = Matrix([[1, 2, 3], [4, 5, 6], [7, 8, 10]])
479 >>> b = Matrix([3, 6, 9])
480 >>> linsolve((A, b), x, y, z)
481 {(-1, 2, 0)}
482 >>> linsolve(Matrix(([1, 1, 1, 1], [1, 1, 2, 3])), (x, y, z))
483 {(-y - 1, y, 2)}
484 The new solve i.e. solveset is under active development and is a planned replace-
485 ment for solve, Hence there are some features which are implemented in solve and is
486 not yet implemented in solveset. The table below show the current state of old and
487 new solve functions.
488

```

Solveset vs Solve		
Feature	solve	solveset
Consistent Output API	No	Yes
Consistent Input API	No	Yes
Univariate	Yes	Yes
Linear System	Yes	Yes (linsolve)
Non Linear System	Yes	Not yet
Transcendental	Yes	Not yet

```

491
492 Below are some of the examples of old solve function:
493     • Non Linear (multivariate) System of Equation: Intersection of a circle and a
494       parabola.
495 >>> solve([x**2 + y**2 - 16, 4*x - y**2 + 6], x, y)
496 [(-2 + sqrt(14), -sqrt(-2 + 4*sqrt(14))),
497  (-2 + sqrt(14), sqrt(-2 + 4*sqrt(14))),
498  (-sqrt(14) - 2, -I*sqrt(2 + 4*sqrt(14))),
499  (-sqrt(14) - 2, I*sqrt(2 + 4*sqrt(14)))]
500     • Transcendental Equation
501 >>> solve((x + log(x))**2 - 5*(x + log(x)) + 6, x)

```

```

502 [LambertW(exp(2)), LambertW(exp(3))]
503 >>> solve(x**3 + exp(x))
504 [-3*LambertW((-1)**(2/3)/3)]

```

505 **4.5. Matrices.** SymPy supports matrices with symbolic expressions as elements.■

```

506 >>> x, y = symbols('x y')
507 >>> A = Matrix(2, 2, [x, x + y, y, x])
508 >>> A
509 Matrix([
510 [x, x + y],
511 [y, x]])

```

512 All SymPy matrix types can do linear algebra including matrix addition, multipli-  
513 cation, exponentiation, computing determinant, solving linear systems, and comput-  
514 ing inverses using LU decomposition, LDL decomposition, Gauss-Jordan elimination,  
515 Cholesky decomposition, Moore-Penrose pseudoinverse, and adjugate matrix.

516 All operations are computed symbolically. Eigenvalues are computed by gener-  
517 ating the characteristic polynomial using the Berkowitz algorithm and then solving  
518 it using polynomial routines. Diagonalizable matrices can be diagonalized first to  
519 compute the eigenvalues.

```

520 >>> A.eigenvals()
521 {x - sqrt(y*(x + y)): 1, x + sqrt(y*(x + y)): 1}

```

522 Internally these matrices store the elements as a list, making it a dense repre-  
523 sentation. For storing sparse matrices, the `SparseMatrix` class can be used. Sparse  
524 matrices store the elements in a dictionary of keys (DoK) format.

525 SymPy also supports matrices with symbolic dimension values. `MatrixSymbol`  
526 represents a matrix with dimensions  $m \times n$ , where  $m$  and  $n$  can be symbolic. Ma-  
527 trix addition and multiplication, scalar operations, matrix inverse, and transpose are  
528 stored symbolically as matrix expressions.

```

529 >>> m, n, p = symbols("m, n, p", integer=True)
530 >>> R = MatrixSymbol("R", m, n)
531 >>> S = MatrixSymbol("S", n, p)
532 >>> T = MatrixSymbol("T", m, p)
533 >>> U = R*S + 2*T
534 >>> U.shape
535 (m, p)
536 >>> U[0, 1]
537 2*T[0, 1] + Sum(R[0, _k]*S[_k, 1], (_k, 0, n - 1))

```

538 Block matrices are also supported in SymPy. `BlockMatrix` elements can be any  
539 matrix expression which includes explicit matrices, matrix symbols, and block matri-  
540 ces. All functionalities of matrix expressions are also present in `BlockMatrix`.

```

541 >>> n, m, l = symbols('n m l')
542 >>> X = MatrixSymbol('X', n, n)
543 >>> Y = MatrixSymbol('Y', m, m)
544 >>> Z = MatrixSymbol('Z', n, m)
545 >>> B = BlockMatrix([[X, Z], [ZeroMatrix(m, n), Y]])
546 >>> B
547 Matrix([
548 [X, Z],
549 [0, Y]])
550 >>> B[0, 0]

```

```

551 X[0, 0]
552 >>> B.shape
553 (m + n, m + n)

```

554 **5. Domain Specific Submodules.** SymPy includes several packages that al-  
555 low users to solve domain specific problems. For example, a comprehensive physics  
556 package is included that is useful for solving problems in classical mechanics, optics,  
557 and quantum mechanics along with support for manipulating physical quantities with  
558 units.

## 559 5.1. Classical Mechanics.

560 **5.1.1. Vector Algebra.** The `sympy.physics.vector` package provides reference  
561 frame, time, and space aware vector and dyadic objects that allow for three dimen-  
562 sional operations such as addition, subtraction, scalar multiplication, inner and outer  
563 products, cross products, etc. Both of these objects can be written in very compact  
564 notation that make it easy to express the vectors and dyadics in terms of multiple  
565 reference frames with arbitrarily defined relative orientations. The vectors are used  
566 to specify the positions, velocities, and accelerations of points, orientations, angular  
567 velocities, and angular accelerations of reference frames, and force and torques. The  
568 dyadics are essentially reference frame aware  $3 \times 3$  tensors. The vector and dyadic  
569 objects can be used for any one-, two-, or three-dimensional vector algebra and they  
570 provide a strong framework for building physics and engineering tools.

571 The following Python interpreter session showing how a vector is created using  
572 the orthogonal unit vectors of three reference frames that are oriented with respect  
573 to each other and the result of expressing the vector in the  $A$  frame. The  $B$  frame  
574 is oriented with respect to the  $A$  frame using Z-X-Z Euler Angles of magnitude  $\pi$ ,  $\frac{\pi}{2}$ ,  
575 and  $\frac{\pi}{3}$  rad, respectively whereas the  $C$  frame is oriented with respect to the  $B$  frame  
576 through a simple rotation about the  $B$  frame's  $X$  unit vector through  $\frac{\pi}{2}$  rad.

```

577 >>> from sympy import pi
578 >>> from sympy.physics.vector import ReferenceFrame
579 >>> A = ReferenceFrame('A')
580 >>> B = ReferenceFrame('B')
581 >>> C = ReferenceFrame('C')
582 >>> B.orient(A, 'body', (pi, pi / 3, pi / 4), 'zxz')
583 >>> C.orient(B, 'axis', (pi / 2, B.x))
584 >>> v = 1 * A.x + 2 * B.z + 3 * C.y
585 >>> v
586 A.x + 2*B.z + 3*C.y
587 >>> v.express(A)
588 A.x + 5*sqrt(3)/2*A.y + 5/2*A.z

```

589 **5.1.2. Mechanics.** The `sympy.physics.mechanics` package utilizes the `sympy.`  
590 `physics.vector` package to populate time aware particle and rigid body objects to  
591 fully describe the kinematics and kinetics of a rigid multi-body system. These objects  
592 store all of the information needed to derive the ordinary differential or differential al-  
593 gebraic equations that govern the motion of the system, i.e., the equations of motion.  
594 These equations of motion abide by Newton's laws of motion and can handle any ar-  
595bitrary kinematical constraints or complex loads. The package offers two automated  
596 methods for formulating the equations of motion based on Lagrangian Dynamics [27]  
597 and Kane's Method [26]. Lastly, there are automated linearization routines for con-  
598 strained dynamical systems based on [36].

**5.2. Symbolic Quantum Mechanics.** The `sympy.physics.quantum` package has extensive capabilities for symbolic quantum mechanics, with Python objects to represent the different mathematical objects relevant in quantum theory [39]: states (bras and kets), operators (unitary, hermitian, etc.) and basis sets as well as operations on these objects such as representations, tensor products, inner products, outer products, commutators, anticommutators, etc. The base objects are designed in the most general way possible to enable any particular quantum system to be implemented by subclassing the base operators to provide system specific logic.

For example, you can define symbolic quantum operators and states and perform a full range of operations with them:

```
>>> from sympy.physics.quantum import Commutator, Dagger, Operator
>>> from sympy.physics.quantum import Ket, qapply
>>> A = Operator('A')
>>> B = Operator('B')
>>> C = Operator('C')
>>> D = Operator('D')
>>> a = Ket('a')
>>> comm = Commutator(A, B)
>>> comm
[A,B]
>>> qapply(Dagger(comm*a)).doit()
-<a|*(Dagger(A)*Dagger(B) - Dagger(B)*Dagger(A))
Commutators can be expanded using common commutator identities:
>>> Commutator(C+B, A*D).expand(commutator=True)
-[A,B]*D - [A,C]*D + A*[B,D] + A*[C,D]
```

On top of this set of base objects, a number of specific quantum systems have been implemented. These include:

- Position/momentum operators and states, raising/lowering operators and states, simple harmonic oscillator, density matrices, hydrogen atom.
- Second quantized formalism of non-relativistic many-body quantum mechanics [19].
- Quantum angular momentum [46]. Spin operators and their eigenstates can be represented in any basis and for any quantum numbers. Facilities for Clebsch-Gordan Coefficients, Wigner Coefficients, rotations, and angular momentum coupling are also present in their symbolic and numerical forms.
- Quantum information and computing [31]. Multidimensional qubit states, and a full set of one- and two-qubit gates are provided and can be represented symbolically or as matrices/vectors. With these building blocks it is possible to implement a number of basic quantum algorithms including the quantum Fourier transform, quantum error correction, quantum teleportation, Grover's algorithm, dense coding, etc.

Here are a few short examples of the quantum information and computing capabilities in `sympy.physics.quantum`. We start with a simple 4 qubit state and flip one of the qubits:

```
>>> from sympy.physics.quantum.qubit import Qubit
>>> q = Qubit('0101')
>>> q
|0101>
>>> q.flip(1)
|0111>
```



```

649 Qubit states can also be used in adjoint operations, tensor products, inner/outer
650 products:
651 >>> Dagger(q)
652 <0101|
653 >>> ip = Dagger(q)*q
654 >>> ip
655 <0101|0101>
656 >>> ip.doit()
657 1
658 Quantum gates (unitary operators) can be applied to transform these states and then
659 classical measurements can be performed on the results:
660 >>> from sympy.physics.quantum.qubit import Qubit, measure_all
661 >>> from sympy.physics.quantum.gate import H, X, Y, Z
662 >>> from sympy.physics.quantum.qapply import qapply
663 >>> c = H(0)*H(1)*Qubit('00')
664 >>> c
665 H(0)*H(1)*|00>
666 >>> q = qapply(c)
667 >>> measure_all(q)
668 [(|00>, 1/4), (|01>, 1/4), (|10>, 1/4), (|11>, 1/4)]

```



Fig. 1: The circuit diagram for a 3-qubit quantum fourier transform generated by SymPy.

```

669 Here is a final example of creating a 3-qubit quantum fourier transform, decomposing
670 it into one- and two-qubit gates, and then generating a circuit plot for the sequence
671 of gates (see Figure 1).
672 >>> from sympy.physics.quantum.qft import QFT
673 >>> from sympy.physics.quantum.circuitplot import circuit_plot
674 >>> fourier = QFT(0,3).decompose()
675 >>> fourier
676 SWAP(0,2)*H(0)*C((0),S(1))*H(1)*C((0),T(2))*C((1),S(2))*H(2)
677 >>> c = circuit_plot(fourier, nqubits=3)

```

678 **6. Conclusion and future work.** SymPy is a robust CAS that provides a wide  
679 array of features. It is written in a general purpose programming language, Python,  
680 which allows it to be used in a first-class way with other Python projects, including

the scientific Python stack. It is designed to be used in an extensible way. Unlike many other CASs, it is designed to be used both as a end-user application and as a library.

SymPy expressions are built from immutable trees of Python classes. It uses Python both as the internal language and the user language, meaning users can use the same methods that the library implements to extend it. SymPy has an assumptions system for declaring and deducing mathematical properties on expressions.

The numerics of SymPy are implemented in the mpmath library, which uses arbitrary precision floating point arithmetic implemented in pure Python. This allows expressions to be evaluated with concrete data as needed.

SymPy has submodules for many areas of mathematics. It has functions for simplifying expressions, doing common calculus operations, pretty printing expressions, solving equations, and symbolic matrices. Other areas also included are discrete math, concrete math, plotting, geometry, statistics, polynomials, sets, series, vectors, combinatorics, group theory, code generation, tensors, Lie algebras, cryptography, and special functions. Additionally, SymPy contains submodules targeting certain specific domains, such as classical mechanics and quantum mechanics.

Some of the planned future work for SymPy includes work on improving code generation, improvements to the speed of SymPy, and improving the solvers module.

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## 9. Supplement.

**9.1. Limits: The Gruntz Algorithm.** SymPy calculates limits using the Gruntz algorithm, as described in [23]. The basic idea is as follows: any limit can be converted to a limit  $\lim_{x \rightarrow \infty} f(x)$  by substitutions like  $x \rightarrow \frac{1}{x}$ . Then the most varying subexpression  $\omega$  (that converges to zero as  $x \rightarrow \infty$  the fastest from all subexpressions) is identified in  $f(x)$ , and  $f(x)$  is expanded into a series with respect to  $\omega$ . Any positive powers of  $\omega$  converge to zero. If there are negative powers of  $\omega$ , then the limit is infinite. The constant term (independent of  $\omega$ , but could depend on  $x$ ) then determines the limit (one might need to recursively apply the Gruntz algorithm on this term to determine the limit).

To determine the most varying subexpression, the comparability classes must first be defined, by calculating  $L$ :

$$(1) \quad L \equiv \lim_{x \rightarrow \infty} \frac{\log |f(x)|}{\log |g(x)|}$$

And then operations  $<$ ,  $>$  and  $\sim$  are defined as follows:  $f > g$  when  $L = \pm\infty$  (it is said that  $f$  is more rapidly varying than  $g$ , i.e.,  $f$  goes to  $\infty$  or 0 faster than  $g$ ,  $f$  is greater than any power of  $g$ ),  $f < g$  when  $L = 0$  ( $f$  is less rapidly varying than  $g$ ) and  $f \sim g$  when  $L \neq 0, \pm\infty$  (both  $f$  and  $g$  are bounded from above and below by suitable integral powers of the other). Here are some examples of comparability classes:

$$\begin{aligned} 2 &< x < e^x < e^{x^2} < e^{e^x} \\ 2 &\sim 3 \sim -5 \\ x &\sim x^2 \sim x^3 \sim \frac{1}{x} \sim x^m \sim -x \\ e^x &\sim e^{-x} \sim e^{2x} \sim e^{x+e^{-x}} \\ f(x) &\sim \frac{1}{f(x)} \end{aligned}$$

The Gruntz algorithm is now illustrated on the following example:

$$(2) \quad f(x) = e^{x+2e^{-x}} - e^x + \frac{1}{x}.$$

The goal is to calculate  $\lim_{x \rightarrow \infty} f(x)$ . First the set of most rapidly varying subexpressions is determined, the so called *mrsv set*. For (2), the following mrsv set  $\{e^x, e^{-x}, e^{x+2e^{-x}}\}$  is obtained. These are all subexpressions of (2) and they all belong to the same comparability class. This calculation can be done using SymPy as follows:

```
>>> from sympy.series.gruntz import mrsv
>>> mrsv(exp(x+2*exp(-x))-exp(x) + 1/x, x)[0].keys()
dict_keys([exp(x + 2*exp(-x)), exp(x), exp(-x)])
```

Next any item  $\omega$  is taken from mrsv that converges to zero for  $x \rightarrow \infty$ . The item  $\omega = e^{-x}$  is obtained. If such a term is not present in the mrsv set (i.e., all terms converge to infinity instead of zero), the relation  $f(x) \sim \frac{1}{f(x)}$  can be used.

Next step is to rewrite the mrsv in terms of  $\omega$ :  $\{\frac{1}{\omega}, \omega, \frac{1}{\omega}e^{2\omega}\}$ . Then the original subexpressions are substituted back into  $f(x)$  and expanded with respect to  $\omega$ :

$$(3) \quad f(x) = \frac{1}{x} - \frac{1}{\omega} + \frac{1}{\omega}e^{2\omega} = 2 + \frac{1}{x} + 2\omega + O(\omega^2)$$

824 Since  $\omega$  is from the mrv set, then in the limit  $x \rightarrow \infty$  it is  $\omega \rightarrow 0$  and so  
825  $2\omega + O(\omega^2) \rightarrow 0$  in (3):

$$826 \quad (4) \quad f(x) = \frac{1}{x} - \frac{1}{\omega} + \frac{1}{\omega} e^{2\omega} = 2 + \frac{1}{x} + 2\omega + O(\omega^2) \rightarrow 2 + \frac{1}{x}$$

827 Since the result  $(2 + \frac{1}{x})$  still depends on  $x$ , the above procedure is iterated on the  
828 result until just a number (independent of  $x$ ) is obtained, which is the final limit. In  
829 the above case the limit is 2, as can be verified by SymPy:

```
830 >>> limit(exp(x+2*exp(-x))-exp(x) + 1/x, x, oo)
831 2
```

832 In general, when  $f(x)$  is expanded in terms of  $\omega$ , it is obtained:

$$833 \quad (5) \quad f(x) = \underbrace{O\left(\frac{1}{\omega^3}\right)}_{\infty} + \underbrace{\frac{C_{-2}(x)}{\omega^2}}_{\infty} + \underbrace{\frac{C_{-1}(x)}{\omega}}_{\infty} + C_0(x) + \underbrace{C_1(x)\omega}_0 + \underbrace{O(\omega^2)}_0$$

834 The positive powers of  $\omega$  are zero. If there are any negative powers of  $\omega$ , then the  
835 result of the limit is infinity, otherwise the limit is equal to  $\lim_{x \rightarrow \infty} C_0(x)$ . The expression  
836  $C_0(x)$  is simpler than  $f(x)$  and so the algorithm always converges. A proof of this, as  
837 well as further details are given in Gruntz's Ph.D. thesis [23].

## 838 9.2. Series.

839 **9.2.1. Series Expansion.** SymPy is able to calculate the symbolic series expansion  
840 of an arbitrary series or expression involving elementary and special functions and  
841 multiple variables. For this it has two different implementations- the `series` method  
842 and Ring Series.

843 The first approach stores a series as an object of the `Basic` class. Each function  
844 has its specific implementation of its expansion which is able to evaluate the Puiseux  
845 series expansion about a specified point. For example, consider a Taylor expansion  
846 about 0:

```
847 >>> from sympy import symbols, series
848 >>> x, y = symbols('x, y')
849 >>> series(sin(x+y) + cos(x*y), x, 0, 2)
850 1 + sin(y) + x*cos(y) + 0(x**2)
```

851 The newer and much faster[1] approach called Ring Series makes use of the ob-  
852 servation that a truncated Taylor series, is in fact a polynomial. Ring Series uses the  
853 efficient representation and operations of sparse polynomials. The choice of sparse  
854 polynomials is deliberate as it performs well in a wider range of cases than a dense  
855 representation. Ring Series gives the user the freedom to choose the type of coeffi-  
856 cients he wants to have in his series, allowing the use of faster operations on certain  
857 types.

858 For this, several low level methods for expansion of trigonometric, hyperbolic and  
859 other elementary functions like inverse of a series, calculating  $n$ th root, etc, are im-  
860 plemented using variants of the Newton[12] Method. All these support Puiseux series  
861 expansion. The following example demonstrates the use of an elementary function  
862 that calculates the Taylor expansion of the sine of a series.

```
863 >>> from sympy import ring
864 >>> from sympy.polys.ring_series import rs_sin
865 >>> R, t = ring('t', QQ)
866 >>> rs_sin(t**2 + t, t, 5)
867 -1/2*t**4 - 1/6*t**3 + t**2 + t
```

868 The function `sympy.polys.rs_series` makes use of these elementary functions to  
 869 expand an arbitrary SymPy expression. It does so by following a recursive strategy  
 870 of expanding the lower most functions first and then composing them recursively to  
 871 calculate the desired expansion. Currently it only supports expansion about 0 and  
 872 is under active development. Ring Series is several times faster than the default  
 873 implementation with the speed difference increasing with the size of the series. The  
 874 `sympy.polys.rs_series` takes as input any SymPy expression and hence there is no  
 875 need to explicitly create a polynomial ring. An example:

```
876 >>> from sympy.polys.ring_series import rs_series
877 >>> from sympy.abc import a, b
878 >>> from sympy import sin, cos
879 >>> rs_series(sin(a + b), a, 4)
880 -1/2*(sin(b))*a**2 + (sin(b)) - 1/6*a**3*(cos(b)) + a*(cos(b))
```

881 **9.2.2. Formal Power Series.** SymPy can be used for computing the Formal  
 882 Power Series of a function. The implementation is based on the algorithm described  
 883 in the paper on Formal Power Series[24]. The advantage of this approach is that an  
 884 explicit formula for the coefficients of the series expansion is generated rather than  
 885 just computing a few terms.

886 The following example shows how to use `fps`:

```
887 >>> f = fps(sin(x), x, x0=0)
888 >>> f.truncate(6)
889 x - x**3/6 + x**5/120 + 0(x**6)
890 >>> f[15]
891 -x**15/1307674368000
```

892 **9.2.3. Fourier Series.** SymPy provides functionality to compute Fourier Series  
 893 of a function using the `fourier_series` function. Under the hood it just computes  $a_0$ ,  
 894  $a_n$ ,  $b_n$  using standard integration formulas.

895 Here's an example on how to compute Fourier Series in SymPy:

```
896 >>> L = symbols('L')
897 >>> f = fourier_series(2 * (Heaviside(x/L) - Heaviside(x/L - 1)) - 1, (x, 0, 2*L))
898 >>> f.truncate(3)
899 4*sin(pi*x/L)/pi + 4*sin(3*pi*x/L)/(3*pi) + 4*sin(5*pi*x/L)/(5*pi)
```

900 **9.3. Logic.** SymPy supports construction and manipulation of boolean expres-  
 901 sions through the `logic` module. SymPy symbols can be used as propositional vari-  
 902 ables and also be substituted as `True` or `False`. A good number of manipulation  
 903 features for boolean expressions have been implemented in the `logic` module.

904 **9.3.1. Constructing boolean expressions.** A boolean variable can be de-  
 905 clared as a SymPy symbol. Python operators `&`, `|` and `~` are overloaded for logical  
 906 And, Or and negate. Several others like `Xor`, `Implies` can be constructed with `^`, `»`  
 907 respectively. The above are just a shorthand, expressions can also be constructed by  
 908 directly calling `And()`, `Or()`, `Not()`, `Xor()`, `Nand()`, `Nor()`, etc.

```
909 >>> from sympy import *
910 >>> x, y, z = symbols('x y z')
911 >>> e = (x & y) | z
912 >>> e.subs({x: True, y: True, z: False})
913 True
```

914 **9.3.2. CNF and DNF.** Any boolean expression can be converted to conjunc-  
 915 tive normal form, disjunctive normal form and negation normal form. The API also

```

916 permits to check if a boolean expression is in any of the above mentioned forms.
917 >>> from sympy.logic.boolalg import is_dnf, is_cnf
918 >>> x, y, z = symbols('x y z')
919 >>> to_cnf((x & y) | z)
920 And(Or(x, z), Or(y, z))
921 >>> to_dnf(x & (y | z))
922 Or(And(x, y), And(x, z))
923 >>> is_cnf((x | y) & z)
924 True
925 >>> is_dnf((x & y) | z)
926 True

```

927 **9.3.3. Simplification and Equivalence.** The module supports simplification  
928 of given boolean expression by making deductions on it. Equivalence of two expres-  
929 sions can also be checked. If so, it is possible to return the mapping of variables of  
930 two expressions so as to represent the same logical behaviour.

```

931 >>> from sympy import *
932 >>> a, b, c, x, y, z = symbols('a b c x y z')
933 >>> e = a & (~a | ~b) & (a | c)
934 >>> simplify(e)
935 And(Not(b), a)
936 >>> e1 = a & (b | c)
937 >>> e2 = (x & y) | (x & z)
938 >>> bool_map(e1, e2)
939 (And(Or(b, c), a), {a: x, b: y, c: z})

```

940 **9.3.4. SAT solving.** The module also supports satisfiability checking of a given  
941 boolean expression. If satisfiable, it is possible to return a model for which the ex-  
942 pression is satisfiable. The API also supports returning all possible models. The SAT  
943 solver has a clause learning DPLL algorithm implemented with watch literal scheme  
944 and VSIDS heuristic[30].

```

945 >>> from sympy import *
946 >>> a, b, c = symbols('a b c')
947 >>> satisfiable(a & (~a | b) & (~b | c) & ~c)
948 False
949 >>> satisfiable(a & (~a | b) & (~b | c) & c)
950 {a: True, b: True, c: True}

```

951 **9.4. Diophantine Equations.** Diophantine equations play a central and an im-  
952 portant role in number theory. A Diophantine equation has the form,  $f(x_1, x_2, \dots, x_n) =$   
953  $0$  where  $n \geq 2$  and  $x_1, x_2, \dots, x_n$  are integer variables. If we can find  $n$  integers  
954  $a_1, a_2, \dots, a_n$  such that  $x_1 = a_1, x_2 = a_2, \dots, x_n = a_n$  satisfies the above equation, we  
955 say that the equation is solvable.

956 Currently, following five types of Diophantine equations can be solved using  
957 SymPy's Diophantine module.

- 958 • Linear Diophantine equations:  $a_1x_1 + a_2x_2 + \dots + a_nx_n = b$
- 959 • General binary quadratic equation:  $ax^2 + bxy + cy^2 + dx + ey + f = 0$
- 960 • Homogeneous ternary quadratic equation:  $ax^2 + by^2 + cz^2 + dxy + eyz + fzx = 0$
- 961 • Extended Pythagorean equation:  $a_1x_1^2 + a_2x_2^2 + \dots + a_nx_n^2 = a_{n+1}x_{n+1}^2$
- 962 • General sum of squares:  $x_1^2 + x_2^2 + \dots + x_n^2 = k$

963 When an equation is fed into Diophantine module, it factors the equation (if

possible) and solves each factor separately. Then all the results are combined to create the final solution set. Following examples illustrate some of the basic functionalities of the Diophantine module.

```

967 >>> from sympy import symbols
968 >>> x, y, z = symbols("x, y, z", integer=True)
969
970 >>> from sympy.solvers.diophantine import *
971 >>> diophantine(2*x + 3*y - 5)
972 set([(3*t_0 - 5, -2*t_0 + 5)])
973
974 >>> diophantine(2*x + 4*y - 3)
975 set()
976
977 >>> diophantine(x**2 - 4*x*y + 8*y**2 - 3*x + 7*y - 5)
978 set([(2, 1), (5, 1)])
979
980 >>> diophantine(x**2 - 4*x*y + 4*y**2 - 3*x + 7*y - 5)
981 set([(-2*t**2 - 7*t + 10, -t**2 - 3*t + 5)])
982
983 >>> diophantine(3*x**2 + 4*y**2 - 5*z**2 + 4*x*y - 7*y*z + 7*z*x)
984 set([(-16*p**2 + 28*p*q + 20*q**2,
985 3*p**2 + 38*p*q - 25*q**2,
986 4*p**2 - 24*p*q + 68*q**2)])
987
988 >>> from sympy.abc import a, b, c, d, e, f
989 >>> diophantine(9*a**2 + 16*b**2 + c**2 + 49*d**2 + 4*e**2 - 25*f**2)
990 set([(70*t1**2 + 70*t2**2 + 70*t3**2 + 70*t4**2 - 70*t5**2, 105*t1*t5,
991 420*t2*t5, 60*t3*t5, 210*t4*t5,
992 42*t1**2 + 42*t2**2 + 42*t3**2 + 42*t4**2 + 42*t5**2)])
993
994 >>> diophantine(a**2 + b**2 + c**2 + d**2 + e**2 + f**2 - 112)
995 set([(8, 4, 4, 4, 0, 0)])

```

**9.5. Sets.** SymPy supports representation of a wide variety of mathematical sets. This is achieved by first defining abstract representations of atomic set classes and then combining and transforming them using various set operations.

Each of the set classes inherits from the base class `Set` and defines methods to check membership and calculate unions, intersections, and set differences. When these methods are not able to evaluate to atomic set classes, they are represented as abstract unevaluated objects.

SymPy has the following atomic set classes:

- `EmptySet` represents the empty set  $\emptyset$ .
- `UniversalSet` is an abstract “universal set” for which everything is a member. The union of the universal set with any set gives the universal set and the intersection gives to the other set itself.
- `FiniteSet` is functionally equivalent to Python’s built `inset` object. Its members can be any SymPy object including other sets themselves.
- `Integers` represents the set of Integers  $\mathbb{Z}$ .
- `Naturals` represents the set of Natural numbers  $\mathbb{N}$ , i.e., the set of positive integers.



- **Naturals0** represents the whole numbers, which are all the non-negative integers.
- **Range** represents a range of integers. A range is defined by specifying a start value, an end value, and a step size. Range is functionally equivalent to Python's `range` except it supports infinite endpoints, allowing the representation of infinite ranges.
- **Interval** represents an interval of real numbers. It is specified by giving the start and end point and specifying if it is open or closed in the respective ends.

Other than unevaluated classes of Union, Intersection and Set Difference operations, we have following set classes.

- **ProductSet** defines the Cartesian product of two or more sets. The product set is useful when representing higher dimensional spaces. For example to represent a three-dimensional space we simply take the Cartesian product of three real sets.
- **ImageSet** represents the image of a function when applied to a particular set. In notation, the image set of a function  $F$  with respect to a set  $S$  is  $\{F(x)|x \in S\}$ . SymPy uses image sets to represent sets of infinite solutions equations such as  $\sin(x) = 0$ .
- **ConditionSet** represents subset of a set whose members satisfies a particular condition. In notation, the condition set of the set  $S$  with respect to the condition  $H$  is  $\{x|H(x), x \in S\}$ . SymPy uses condition sets to represent the set of solutions of equations and inequalities, where the equation or the inequality is the condition and the set is the domain being solved over.

A few other classes are implemented as special cases of the classes described above. The set of real numbers, **Reals** is implemented as a special case of **Interval**,  $(-\infty, \infty)$ . **ComplexRegion** is implemented as a special case of **ImageSet**. **ComplexRegion** supports both polar and rectangular representation of regions on the complex plane.

**9.6. SymPy Gamma.** SymPy Gamma is a simple web application that runs on Google App Engine. It executes and displays the results of SymPy expressions as well as additional related computations, in a fashion similar to that of Wolfram|Alpha. For instance, entering an integer will display its prime factors, digits in the base-10 expansion, and a factorization diagram. Entering a function will display its docstring; in general, entering an arbitrary expression will display its derivative, integral, series expansion, plot, and roots.

SymPy Gamma also has several additional features than just computing the results using SymPy.

- It displays integration steps, differentiation steps in detail, which can be viewed in Figure 2:



Fig. 2: Integral steps of  $\tan(x)$

- It also displays the factor tree diagrams for different numbers.
- SymPy Gamma also saves user search queries, and offers many such similar features for free, which Wolfram|Alpha only offers to its paid users.

Every input query from the user on SymPy Gamma is first, parsed by its own parser, which handles several different forms of function names, which SymPy as a library doesn't support. For instance, SymPy Gamma supports queries like `sin x`, whereas SymPy doesn't support this, and supports only `sin(x)`.

This parser converts the input query to the equivalent SymPy readable code, which is then eventually processed by SymPy and the result is finally formatted in LaTeX and displayed on the SymPy Gamma web-application.

**9.7. SymPy Live.** SymPy Live is an online Python shell, which runs on Google App Engine, that executes SymPy code. It is integrated in the SymPy documentation examples, located at this [link](#).

This is accomplished by providing a HTML/JavaScript GUI for entering source code and visualization of output, and a server part which evaluates the requested source code. It's an interactive AJAX shell, that runs SymPy code using Python on the server.

Certain Features of SymPy Live:

- It supports the exact same syntax as SymPy, hence it can be used easily, to test for outputs of various SymPy expressions.
- It can be run as a standalone app or in an existing app as an admin-only handler, and can also be used for system administration tasks, as an interactive way to try out APIs, or as a debugging aid during development.
- It can also be used to plot figures ([link](#)), and execute all kinds of expressions that SymPy can evaluate.
- SymPy Live also formats the output in LaTeX for pretty-printing the output.

**9.8. Comparison with Mathematica.** Wolfram Mathematica is a popular proprietary CAS. It features highly advanced algorithms. Mathematica has a core implemented in C++ [6] which interprets its own programming language (known as Wolfram language).

Analogously to Lisp’s S-expressions, Mathematica uses its own style of M-expressions, which are arrays of either atoms or other M-expression. The first element of the expression identifies the type of the expression and is indexed by zero, whereas the first argument is indexed by one. Notice that SymPy expression arguments are stored in a Python tuple (that is, an immutable array), while the expression type is identified by the type of the object storing the expression.

Mathematica can associate attributes to its atoms. Attributes may define mathematical properties and behavior of the nodes associated to the atom. In SymPy, the usage of static class fields is roughly similar to Mathematica’s attributes, though other programming patterns may also be used to achieve an equivalent behavior, such as class inheritance.

Unlike SymPy, Mathematica’s expressions are mutable, that is one can change parts of the expression tree without the need of creating a new object. The reactivity of Mathematica allows for a lazy updating of any references to that data structure.

Products in Mathematica are determined by some builtin node types, such as `Times`, `Dot`, and others. `Times` is overloaded by the `*` operator, and is always meant to represent a commutative operator. The other notable product is `Dot`, overloaded by the `.` operator. This product represents matrix multiplication, it is not commutative. SymPy uses the same node for both scalar and matrix multiplication, the only exception being with abstract matrix symbols. Unlike Mathematica, SymPy determines commutativity with respect to multiplication from the factor’s expression type. Mathematica puts the `Orderless` attribute on the expression type.

Regarding associative expressions, SymPy handles associativity by making associative expressions inherit the class `AssocOp`, while Mathematica specifies the `Flat` attribute on the expression type.

Mathematica relies heavily on pattern matching: even the so-called equivalent of function declaration is in reality the definition of a pattern matching generating an expression tree transformation on input expressions. Mathematica’s pattern matching is sensitive to associative[2], commutative[3], and one-identity[4] properties of its expression tree nodes[5]. SymPy has various ways to perform pattern matching. All of them play a lesser role in the CAS than in Mathematica and are basically available as a tool to rewrite expressions. The differential equation solver in SymPy somewhat relies on pattern matching to identify the kind of differential equation, but it is envisaged to replace that strategy with analysis of Lie symmetries in the future. Mathematica’s real advantage is the ability to add new overloading to the expression builder at runtime, or for specific subnodes. Consider for example

```
In[1]:= Unprotect[Plus]
```

```

1120
1121 Out[1]= {Plus}
1122
1123 In[2]:= Sin[x_]^2 + Cos[y_]^2 := 1
1124
1125 In[3]:= x + Sin[t]^2 + y + Cos[t]^2
1126
1127 Out[3]= 1 + x + y
1128 This expression in Mathematica defines a substitution rule that overloads the func-
1129 tionality of the Plus node (the node for additions in Mathematica). The trailing
1130 underscore after a symbol means that it is to be considered a wildcard. This example
1131 may not be practical, one may wish to keep this identity unevaluated, nevertheless
1132 it clearly illustrates the potentiality to define one's own immediate transformation
1133 rules. In SymPy the operations constructing the addition node in the expression tree
1134 are Python class constructors, and cannot be modified at runtime.5 The way SymPy
1135 deals with extending the missing runtime overloadability functionality is by subclass-
1136 ing the node types. Subclasses may overload the class constructor to yield the proper
1137 extended functionality.
1138 Unlike SymPy, Mathematica does not support type inheritance or polymorphism [17].
1139 SymPy relies heavily on class inheritance, but for the most part, class inheritance is
1140 used to make sure that SymPy objects inherit the proper methods and implement the
1141 basic hashing system. Associativity of expressions can be achieved by inheriting the
1142 class AssocOp, which may appear a more cumbersome operation than Mathematica's
1143 attribute setting.
1144 Matrices in SymPy are types on their own. In Mathematica, nested lists are
1145 interpreted as matrices whenever the sublists have the same length. The main differ-
1146 ence to SymPy is that ordinary operators and functions do not get generalized the
1147 same way as used in traditional mathematics. Using the standard multiplication in
1148 Mathematica performs an elementwise product, this is compatible with Mathemat-
1149 ica's convention of commutativity of Times nodes. Matrix product is expressed by
1150 the dot operator, or the Dot node. The same is true for the other operators, and
1151 even functions, most notably calling the exponential function Exp on a matrix returns
1152 an elementwise exponentiation of its elements. The real matrix exponentiationl is
1153 available through the MatrixExp function.
1154 Unevaluated expressions can be achieved in various ways, most commonly with
1155 the HoldForm or Hold nodes, that block the evaluation of subnodes by the parser.
1156 Note that such a node cannot be expressed in Python, because of greedy evaluation.
1157 Whenever needed in SymPy, it is necessary to add the parameter evaluate=False to
1158 all subnodes, or put the input expression in a string.
1159 The operator == returns a boolean whenever it is able to immediately evaluate
1160 the truthness of the equality, otherwise it returns an Equal expression. In SymPy ==
1161 means structural equality and is always guaranteed to return a boolean expression.
1162 To express an equality in SymPy it is necessary to explicitly construct the Equality
1163 class.
1164 SymPy, in accordance with Python and unlike the usual programming convention,
1165 uses ** to express the power operator, while Mathematica uses the more common ^.

```

---

<sup>5</sup>In reality, Python supports monkey patching, nonetheless it is a discouraged programming pattern.

**9.9. Other Projects that use SymPy.** There are several projects that use SymPy as a library for implementing a part of their project, or even as a part of back-end for their application as well.

Some of them are listed below:

- **Cadabra**: Cadabra is a symbolic computer algebra system (CAS) designed specifically for the solution of problems encountered in field theory.
- **Octave Symbolic**: The Octave-Forge Symbolic package adds symbolic calculation features to GNU Octave. These include common Computer Algebra System tools such as algebraic operations, calculus, equation solving, Fourier and Laplace transforms, variable precision arithmetic and other features.
- **SymPy.jl**: Provides a Julia interface to SymPy using PyCall.
- **Mathics**: Mathics is a free, general-purpose online CAS featuring Mathematica compatible syntax and functions. It is backed by highly extensible Python code, relying on SymPy for most mathematical tasks.
- **Mathpix**: An iOS App, that uses Artificial Intelligence to detect handwritten math as input, and uses SymPy Gamma, to evaluate the math input and generate the relevant steps to solve the problem.
- **IKFast**: IKFast is a robot kinematics compiler provided by **OpenRAVE**. It analytically solves robot inverse kinematics equations and generates optimized C++ files. It uses SymPy for its internal symbolic mathematics.
- **Sage**: A CAS, visioned to be a viable free open source alternative to Magma, Maple, Mathematica and Matlab.
- **SageMathCloud**: SageMathCloud is a web-based cloud computing and course management platform for computational mathematics.
- **PyDy**: Multibody Dynamics with Python.
- **galgebra**: Geometric algebra (previously sympy.galgebra).
- **yt**: Python package for analyzing and visualizing volumetric data (yt.units uses SymPy).
- **SfePy**: Simple finite elements in Python, see Section 9.10.1.
- **Quameon**: Quantum Monte Carlo in Python.
- **Lcapy**: Experimental Python package for teaching linear circuit analysis.
- **Quantum Programming in Python**: Quantum 1D Simple Harmonic Oscillator and Quantum Mapping Gate.
- **LaTeX Expression project**: Easy LaTeX typesetting of algebraic expressions in symbolic form with automatic substitution and result computation.
- **Symbolic statistical modeling**: Adding statistical operations to complex physical models.

**9.10. Project Details.** Below we provide particular examples of SymPy use in some of the projects listed above.

**9.10.1. SfePy.** **SfePy** (Simple finite elements in Python), cf. [16], is a Python package for solving partial differential equations (PDEs) in 1D, 2D and 3D by the finite element (FE) method [47]. SymPy is used within this package mostly for code generation and testing, namely:

- generation of the hierarchical FE basis module, involving generation and symbolic differentiation of 1D Legendre and Lobatto polynomials, constructing the FE basis polynomials [41] and generating the C code;
- generation of symbolic conversion formulas for various groups of elastic constants [21] – provide any two of the Young’s modulus, Poisson’s ratio, bulk modulus, Lamé’s first parameter, shear modulus (Lamé’s second parameter)

- or longitudinal wave modulus and get the other ones;
- simple physical unit conversions, generation of consistent unit sets;
- testing FE solutions using method of manufactured (analytical) solutions – the differential operator of a PDE is symbolically applied and a symbolic right-hand side is created, evaluated in quadrature points, and subsequently used to obtain a numerical solution that is then compared to the analytical one;
- testing accuracy of 1D, 2D and 3D numerical quadrature formulas (cf. [7]) by generating polynomials of suitable orders, integrating them, and comparing the results with those obtained by the numerical quadrature.

**9.11. Tensors.** Ongoing work to provide the capabilities of tensor computer algebra has so far produced the `tensor` module. It is composed of three separated sub-modules, whose purposes are quite different: `tensor.indexed` and `tensor.indexed_methods` support indexed symbols, `tensor.array` contains facilities to operator on symbolic  $N$ -dimensional arrays and finally `tensor.tensor` is used to define abstract tensors. The abstract tensors subsection is inspired by xAct[29] and Cadabra[34]. Canonicalization based on the Butler-Portugal[28] algorithm is supported in SymPy. It is currently limited to polynomial tensor expressions.