

# SYMPY: SYMBOLIC COMPUTING IN PYTHON

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## 1. Introduction.

## 2. Architecture.

**2.1. 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  $xy + 2$ :

```
>>> from sympy import *
>>> x, y = symbols('x y')
>>> expr = x*y + 2
```

The expression `expr` is an addition, so it is of type `Add`. The child nodes of `expr` are `x*y` and `2`.

```
>>> 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` gives a string representing a valid Python code, containing all the nested class constructor calls to create the given expression.

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

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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 mathematical equality. This allows one to test if any two expressions are equal to one another as expression trees.

Python allows classes to overload operators. The Python interpreter translates the above `x*y + 2` to, roughly, `(x.__mul__(y)).__add__(2)`. `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, 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.

**2.2. 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.

```
>>> x = Symbol('x')
>>> sqrt(x**2)
sqrt(x**2)
```

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

Assumptions are set on `Symbol` objects when they are created. For instance `Symbol('x', positive=True)` will create a symbol named `x` that is assumed to be positive.

```
>>> x = Symbol('x', positive=True)
>>> sqrt(x**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`.

82 **x**

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

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

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

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

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

108 **2.3. Extensibility.** Extensibility is an important feature for SymPy. Because  
109 the same language, Python, is used both for the internal implementation and the  
110 external usage by users, all the extensibility capabilities available to users are also  
111 used by functions that are part of SymPy.

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

120 The `Function` class is a subclass of `Expr` which makes it easier to define math-  
121 ematical functions called with arguments. This includes named functions like `sin(x)`  
122 and `log(x)` as well as undefined functions like `f(x)`. Subclasses of `Function` should  
123 define a class method `eval`, which returns values for which the function should be  
124 automatically evaluated, and `None` for arguments that shouldn't be automatically  
125 evaluated.

126 The behavior of classes in SymPy with various other SymPy functions is de-

---

<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.

finned by defining a relevant `_eval_*` method on the class. For instance, an object can tell SymPy's `diff` function how to take the derivative of itself by defining the `_eval_derivative(self, x)` method. 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. Algorithms.

**3.1. 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 evaluate to `double` (53-bit) precision, strings should be used to input precise decimal





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 [23]; 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 cancellations (amounting to 656 bits of precision when  $x = 10000$ ), giving correct values:

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

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

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

We highlight the generalized hypergeometric functions and the Meijer G-function, due to those functions' frequent appearance in closed forms for integrals and sums [todo: crossref symbolic integration]. Via mpmath, SymPy has relatively good support for evaluating sums and integrals numerically, using two complementary approaches: direct numerical evaluation, or first computing a symbolic closed form involving special functions. [example?]

**3.1.3. Numerical simplification.** The `nsimplify` function in SymPy (a wrapper of `identify` in mpmath) attempts to find a simple symbolic expression that evaluates to the same numerical value as the given input. It works by applying a few simple transformations (including square roots, reciprocals, logarithms and exponentials) to the input and, for each transformed value, using the PSLQ algorithm [9] to search for a matching algebraic number or optionally a linear combination of user-provided base constants (such as  $\pi$ ).

```
>>> x = 1 / (sin(pi/5)+sin(2*pi/5)+sin(3*pi/5)+sin(4*pi/5))**2
>>> nsimplify(x)
-2*sqrt(5)/5 + 1
>>> nsimplify(pi, tolerance=0.01)
22/7
>>> nsimplify(1.783919626661888, [pi], tolerance=1e-12)
pi/(-1/3 + 2*pi/3)
```

## 3.2. Polynomials.

## 3.3. The Risch Algorithm.

**3.4. The Gruntz Algorithm.** The limit module implements the Gruntz algorithm [12].

Examples:

```
In [1]: limit(sin(x)/x, x, 0)
Out[1]: 1

In [2]: limit((2**((1-cos(x))/sin(x))-1)**(sinh(x)/atan(x)**2), x, 0)
Out[2]: E
```

316 **3.4.1. Details.** We first define comparability classes by calculating  $L$ :

317 (1) 
$$L \equiv \lim_{x \rightarrow \infty} \frac{\log |f(x)|}{\log |g(x)|}$$

318 And then we define the  $<$ ,  $>$  and  $\sim$  operations as follows:  $f > g$  when  $L = \pm\infty$  ( $f$   
319 is more rapidly varying than  $g$ , i.e.,  $f$  goes to  $\infty$  or  $0$  faster than  $g$ ,  $f$  is greater than  
320 any power of  $g$ ),  $f < g$  when  $L = 0$  ( $f$  is less rapidly varying than  $g$ ) and  $f \sim g$  when  
321  $L \neq 0, \pm\infty$  (both  $f$  and  $g$  are bounded from above and below by suitable integral  
322 powers of the other).

Examples:

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

The Gruntz algorithm, on an example:

$$\begin{aligned} f(x) &= e^{x+2e^{-x}} - e^x + \frac{1}{x} \\ \lim_{x \rightarrow \infty} f(x) &=? \end{aligned}$$

323 Strategy: mrv set: the set of most rapidly varying subexpressions  $\{e^x, e^{-x}, e^{x+2e^{-x}}\}$ ,  
324 the same comparability class. Take an item  $\omega$  from mrv, converging to 0 at infinity.  
325 Here  $\omega = e^{-x}$ . If not present in the mrv set, use the relation  $f(x) \sim \frac{1}{f(x)}$ .

Rewrite the mrv set using  $\omega$ :  $\{\frac{1}{\omega}, \omega, \frac{1}{\omega}e^{2\omega}\}$ , substitute back into  $f(x)$  and expand in  $\omega$ :

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

The core idea of the algorithm:  $\omega$  is from the mrv set, so in the limit  $\omega \rightarrow 0$ :

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

326 We iterate until we get just a number, the final limit. Gruntz proved this algo-  
327 rithm always works and converges in his Ph.D. thesis [12].

Generally:

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

328 we look at the lowest power of  $\omega$ . The limit is one of:  $0, \lim_{x \rightarrow \infty} C_0(x), \infty$ .

329 **3.5. Logic.**

330 **3.6. Other.**



**4. Features.** SymPy has an extensive feature set that encompasses too much to cover in-depth here. Bedrock areas, such as Calculus, receive their own sub-sections below. Additionally, Table 1 describes other capabilities present in the SymPy code base. This gives a sampling from the breadth of topics and application domains that SymPy services.

Table 1: SymPy Features and Descriptions

Feature	Description
Discrete Math	Summations, products, binomial coefficients, prime number tools, integer factorization, Diophantine equation solving, and boolean logic representation, equivalence testing, and inference.
Concrete Math	Tools for determining whether summation and product expressions are convergent, absolutely convergent, hypergeometric, and other properties. May also compute Gosper's normal form [20] for two univariate polynomials.
Plotting	Hooks for visualizing expressions via matplotlib [?] or as text drawings when lacking a graphical back-end.
Geometry	Allows the creation of 2D geometrical entities, such as lines and circles. Enables queries on these entities, including asking the area of an ellipse, checking for collinearity of a set of points, or finding the intersection between two lines.
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.
Polynomials	Computes polynomial algebras over various coefficient domains ranging from the simple (e.g., polynomial division) to the advanced (e.g., Gröbner bases [3] and multivariate factorization over algebraic number domains).
Sets	Representations of empty, finite, and infinite sets. This includes special sets such as for all natural, integer, and complex numbers.
Series	Implements series expansion, sequences, and limit of sequences. This includes special series, such as Fourier and power series.
Vectors	Provides basic vector math and differential calculus with respect to 3D Cartesian coordinate systems.
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).
Combinatorics & Group Theory	Implements permutations, combinations, partitions, subsets, various permutation groups (such as polyhedral, Rubik, symmetric, and others), Gray codes [18], and Prufer sequences [6].
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.
Tensors	Symbolic manipulation of indexed objects.
Lie Algebras	Represents Lie algebras and root systems.

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
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.

## 4.1. Basic Operations.

### 4.1.1. Expression manipulation.

Symbols are instances of the class `Symbol`. They may be declared by invoking the class constructor with the symbol string representation, or through the faster `symbols` and `var` functions.

Common functions for polynomial expression manipulations are listed in the following table:

	<code>expand</code>	expand the expression
	<code>factor</code>	recognize factors
341	<code>collect</code>	.
	<code>together</code>	.
	<code>apart</code>	.

The generic way to simplify an expression is by calling the `simplify` function, or equivalently, calling it as a method `expr.simplify()`. It must be emphasized that simplification is not an unambiguously defined mathematica operation, nevertheless full simplification may require a huge amount of computational power.

There are specific algorithms for special simplification cases, such as `fu`, which calls a powerful simplification algorithm for trigonometric expressions [10]. For trigonometric expressions there is furthermore a `trigsimp` method, acting as a wrapper for specific algorithms. `sqrtdenest` may help by denesting square roots inside other square roots.

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

`.replace` provides more basic matching algorithm, though it allows for custom matching functions to be passed to it.

`.xreplace` is an expression tree structural replacement routing, unaware of any mathematical property.

Expression constructors accept in most cases the boolean parameter `evaluate`, setting it to false will prevent automatic evaluation of the expression. The `global_evaluate` variable may be employed to globally block any kind of evaluation.

### 4.1.2. Assumptions system.

SymPy has two assumptions systems, referred to as new-style and old-style assumptions.

In the old-style assumptions system propositions are assigned to symbols upon class construction, for example, to declare the symbol  $i$  as positive integer, one would call

```
i = Symbol("i", integer=True, positive=True)
```

querying the assumptions is handled through attributes

```

368 i.is_positive
369 i.is_integer
370     These methods return either a boolean, indicating whether the preposition is true
371 or false, or a None, when it is impossible to determine the truth value of the queried
372 preposition.
373     Despite the fact that assumptions can only be declared on symbols, querying can
374 happen on every expression.
375 In [1]: x,y = symbols('x y', positive=True)
376
377 In [2]: (x*y).is_positive
378 Out[2]: True
379
380 In [3]: z = symbols('z')
381
382 In [4]: (x*z).is_positive
383
384 In [5]: w = symbols('w', positive=False)
385
386 In [6]: (x*w).is_positive
387 Out[6]: False
388     The output 2 is true because SymPy's algorithms can deduce that the product of
389 two positive numbers is positive, while there is no output for input 4, as the symbol
390 z doesn't have any information about its sign, and the product  $x \cdot z$  may be positive
391 as well as negative. Finally, output 6 is false as the product of positive and negative
392 numbers is negative.
393     The new-style assumptions are an assumptions system that exists alongside with
394 the old-style, but is significantly different in the way predicates are used. Predicates
395 in the new-style assumptions system are located under the  $Q$  namespace, they appear
396 as Q.positive, Q.integer and so on.
397     Querying is provided through the ask functions. The previous example in the
398 new-style assumptions can be written as
399 In [1]: ask(Q.positive(x*y), Q.positive(x) & Q.positive(y))
400 Out[1]: True
401
402 In [2]: ask(Q.positive(x*y), Q.positive(x))
403
404 In [3]: ask(Q.positive(x*y), Q.positive(x) & Q.negative(y))
405 Out[3]: False
406 That is, ask returns the truth value of its first parameter assuming that its latter
407 argument is true.
408     Expressions like Q.positive are instances of the class Predicate, while the same
409 expression with a parameter, such as Q.positive(x) is an instance of AppliedPredicate.
410     Logical connectors can be expressed through operator overloading, such as in
411 Q.positive(x) & Q.positive(y), or by directly constructing the identical expres-
412 sion through the logical connector class, in this case And(Q.positive(x), Q.positive(y)).
413
414 4.1.3. Calculus. Derivations can be computed with the diff function, or using
415 the method with the same name on the expressions:
416 In [1]: diff(sin(x), x)
417 Out[1]: cos(x)

```

```

417
418 In [2]: sin(x).diff(x)
419 Out[2]: cos(x)
420     The class Derivative is a container for unevaluated derivatives
421 In [3]: expr = Derivative(sin(x), x)
422
423 In [4]: expr
424 Out[4]:
425 d
426 --(sin(x))
427 dx
428     To evaluate such a held expression, simply call the doit method:
429 In [5]: expr.doit()
430 Out[5]: cos(x)
431     Integrals can be analogously calculated either with the integrate function or
432 with the method with the same name on expressions:
433 >>> integrate(sin(x), x)
434 -cos(x)
435 This expression returns an expression whose derivative is the original expression. No-
436 tice that integrals are defined up to an integration constant, for the sake of simplicity
437 SymPy will not display the full generic expression.
438     Definite integration can be calculated with the same method, by specifying a
439 range of the integration variable:
440 >>> integrate(sin(x), (x, 0, 1))
441 -cos(1) + 1
442     To express unevaluated integrals, the class Integral may help
443 Integral(sin(x), x)
444 as in the case of derivatives, the method doit will cause such an expression to be
445 evaluated.
446     Limits:
447 In [9]: limit(sin(x)/x, x, 0)
448 Out[9]: 1
449 for unevaluated expressions, Limit.
450     TODO: right and left limits.
451     Sums and products are handled by the Sum and Product classes, respectively.
452 Analogously with Integral, the first argument is the expression to be summed over,
453 whereas the following arguments represent the summation and multiplication indices,
454 respectively, provided with integer ranges.
455     It may be noted the existence of the IndexedBase class, which provides the con-
456 struction of indexed symbols, that is symbols that are treated as different if their
457 indices are different.

```

458 **4.1.4. Expression outputs.** Alongside with its parsers, SymPy has a rich col-  
459 lection of expression printers.

460 Expressions may be readily transformed into a LaTeX form with the `latex( )`  
461 function.

462 Pretty printer outputs the expression in traditional form with characters, outputs  
463 can be visualized in monospace fonts.

464 **4.2. Calculus.**

**4.3. Sets.** SymPy supports representation of a wide variety of sets, this is achieved by first defining abstract representation for a smaller number of atomic set classes and then combining and transforming them using various set operations.

Each of the set classes inherits from the base set class and defines rules to check membership of a SymPy object in that set, to calculate union, intersection and set difference. In cases we are not able to evaluate these operations to atomic set classes they are represented as abstract unevaluated objects.

We have the following atomic set classes in SymPy.

- **EmptySet**: represents the empty set  $\emptyset$ .
- **UniversalSet**: Everything is a member of Universal Set. Union of Universal Set with any set gives Universal Set and intersection leads to the other set itself.
- **FiniteSet** is functionally equivalent to python's set object. Its members can be any SymPy object including other sets themselves.
- **Integers** represents set of Integers  $\mathbb{Z}$ .
- **Naturals** represents set of Natural numbers  $\mathbb{N}$  i.e., set of positive integers.
- **Naturals0** represents the whole numbers which are all the non-negative integers, inclusive of zero.
- **Range** represents a range of integers and is defined by specifying a start value, an end value and a step size. Range is functionally equivalent to python's range except the fact that it accepts infinity at end points allowing us to represent infinite ranges.
- **RealInterval** is specified by giving the start and end point and specifying if it is open or closed in the respective ends. The set of real numbers is represented as a special case of a real interval where the start point is negative infinite and the end point is positive infinite.

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

- **ProductSet** abstractly defines the Cartesian product of two or more sets. 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 Image Set of a function  $F$  w.r.t a set  $S$  is  $\{F(x)|x \in S\}$  In particular we use Image Set to represent the set of infinite solutions from trigonometric equations.
- **ConditionSet** represents subset of a set who's members satisfies a particular condition. In notation Condition Set of set  $S$  w.r.t to a condition  $H$  is  $\{x|H(x), x \in S\}$ . We use Condition Set to represent the set of solutions of an equation or an inequality where the equation or the inequality is the condition and the set is the domain in which we aim to find the solution.

A few other classes are implemented as special cases of the classes described above. The real number **Reals** is implemented as a special case of real interval where the start point is negative infinity and the end point is positive infinity. **ComplexRegion** is implemented as a special case of **ImageSet**, **ComplexRegion** supports both polar and rectangular representation of region on the complex plane.

**4.4. Solvers.** SymPy has module of equation solvers for symbolic equations. There are two submodules to solve algebraic equations in SymPy, referred to as old solve function, **solve**, and new solve function, **solveset**. Solveset is introduced with

several design changes with respect to old `solve` function to resolve the issues with old `solve` function, for example old `solve` function's input API has many flags which are not needed and they make it hard for the user and the developers to work on solvers. In contrast to old `solve` function, the `solveset` has a clean input API, It only asks for the much needed information from the user, following are the function signatures of old and new `solve` function:

```

520 solve(f, *symbols, **flags) # old solve function
521 solveset(f, symbol, domain) # new solve function

```

The old `solve` function has an inconsistent output API for various types of inputs, whereas the `solveset` has a canonical output API which is achieved using sets. It can consistently return various types of solutions.

- Single solution

```

526 >>> solveset(x - 1)
527 >>> {1}

```

- Finite set of solution, quadratic equation

```

529 >>> solveset(x**2 - pi**2, x)
530 {-pi, pi}

```

- No Solution

```

532 >>> solveset(1, x)
533 EmptySet()

```

- Interval of solution

```

535 >>> solveset(x**2 - 3 > 0, x, domain=S.Reals)
536 (-oo, -sqrt(3)) U (sqrt(3), oo)

```

- Infinitely many solutions

```

538 >>> solveset(sin(x) - 1, x, domain=S.Reals)
539 ImageSet(Lambda(_n, 2*_n*pi + pi/2), Integers())
540 >>> solveset(x - x, x, domain=S.Reals)
541 (-oo, oo)
542 >>> solveset(x - x, x, domain=S.Complexes)
543 S.Complexes

```

- Linear system: finite and infinite solution for determined, under determined and over determined problems.

```

546 >>> A = Matrix([[1, 2, 3], [4, 5, 6], [7, 8, 10]])
547 >>> b = Matrix([3, 6, 9])
548 >>> linsolve((A, b), x, y, z)
549 {(-1,2,0)}
550 >>> linsolve(Matrix([[1, 1, 1, 1], [1, 1, 2, 3]]), (x, y, z))
551 {(-y - 1, y, 2)}

```

The new `solve` i.e. **`solveset`** is under active development and is a planned replacement for **`solve`**, Hence there are some features which are implemented in `solve` and is not yet implemented in `solveset`. The table below show the current state of old and new `solve` functions.

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

Below are some of the examples of old **solve** function:

- Non Linear (multivariate) System of Equation: Intersection of a circle and a parabola.

```
>>> solve([x**2 + y**2 - 16, 4*x - y**2 + 6], x, y)
[(-2 + sqrt(14), -sqrt(-2 + 4*sqrt(14))),
 (-2 + sqrt(14), sqrt(-2 + 4*sqrt(14))),
 (-sqrt(14) - 2, -I*sqrt(2 + 4*sqrt(14))),
 (-sqrt(14) - 2, I*sqrt(2 + 4*sqrt(14)))]
```

- Transcendental Equation

```
>>> solve(x + log(x)**2 - 5*(x + log(x)) + 6, x)
[LambertW(exp(2)), LambertW(exp(3))]
>>> solve(x**3 + exp(x))
[-3*LambertW((-1)**(2/3)/3)]
```

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

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

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

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.

```
>>> from sympy import symbols
>>> x, y, z = symbols("x, y, z", integer=True)

>>> diophantine(2*x + 3*y - 5)
set([(3*t_0 - 5, -2*t_0 + 5)])

>>> diophantine(2*x + 4*y - 3)
set()

>>> diophantine(x**2 - 4*x*y + 8*y**2 - 3*x + 7*y - 5)
set([(2, 1), (5, 1)])
```



```

600 >>> diophantine(x**2 - 4*x*y + 4*y**2 - 3*x + 7*y - 5)
601 set([(-2*t**2 - 7*t + 10, -t**2 - 3*t + 5)])
602
603 >>> diophantine(3*x**2 + 4*y**2 - 5*z**2 + 4*x*y - 7*y*z + 7*z*x)
604 set([(-16*p**2 + 28*p*q + 20*q**2, 3*p**2 + 38*p*q - 25*q**2, 4*p**2 - 24*p*q + 68*q**2)])
605
606 >>> from sympy.abc import a, b, c, d, e, f
607 >>> diophantine(9*a**2 + 16*b**2 + c**2 + 49*d**2 + 4*e**2 - 25*f**2)
608 set([(70*t1**2 + 70*t2**2 + 70*t3**2 + 70*t4**2 - 70*t5**2, 105*t1*t5, 420*t2*t5, 60*t3*t5, 210*t4*t5, 4
609
610 >>> diophantine(a**2 + b**2 + c**2 + d**2 + e**2 + f**2 - 112)
611 set([(8, 4, 4, 4, 0, 0)])

```

612 **4.5. Matrices.** SymPy supports matrices with symbolic expressions as elements.■

613 There are two types of matrices, Mutable and Immutable. Mutable classes are the  
614 default in SymPy as mutability is important for performance, but it means that stan-  
615 dard matrices can not interact well with the rest of SymPy. This is because the Basic  
616 object, from which most SymPy classes inherit, is immutable.

617 Immutable matrix classes inherit from Basic and can thus interact more naturally  
618 with the rest of SymPy.

619 In [1]: from sympy import Matrix, symbols, MatrixSymbol

620

621 In [2]: x, y = symbols('x y', positive=True)

622

623 In [3]: t = Matrix(2, 2, [x, x + y, y, x])

624

625 In [4]: t

626

627 Out[4]:

```

628 Matrix([
629 [ x, x + y],
630 [ y, x]])

```

631

632 In [5]: t[0, 1] = y

633

634 In [6]: t

635 Out[6]:

```

636 Matrix([
637 [x, y],
638 [y, x]])

```

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

643 Eigenvalues are computed symbolically as well. Eigenvalues are computed by gen-  
644 erating the characteristic polynomial using the Berkowitz algorithm and then solving  
645 it using polynomial routines. Diagonalizable matrices can be diagonalized first to  
646 compute the eigenvalues.

647 In [10]: t.eigenvals()

648 Out[10]: {x - y: 1, x + y: 1}

Internally these matrices store the elements as a list making it a dense representation. For storing sparse matrices, `SparseMatrix` and `ImmutableSparseMatrix` classes can be used. Sparse matrix classes store the elements in Dictionary of Keys (DoK) format.

SymPy also supports matrices with unknown dimension values. `MatrixSymbol` represents a matrix with dimensions `m`, `n` where `m` and `n` can be symbols or integers. Matrix addition and multiplication, scalar operations, matrix inverse and transpose are stored symbolically as matrix expressions. Mutable matrices are converted to corresponding immutable types before interacting with matrix expressions

```
In [11]: m, n, p = symbols("m, n, p", integer=True)
In [12]: r, s = MatrixSymbol("r", m, n), MatrixSymbol("s", n, p)
In [13]: u = r * s + 2*MatrixSymbol("t", m, p)
In [14]: u.shape
Out[14]: (m, p)
In [15]: u[0, 1]
Out[15]: 2*t[0, 1] + Sum(r[0, _k]*s[_k, 1], (_k, 0, n - 1))
```

Block matrices are also supported in SymPy. `BlockMatrix` elements can be any matrix expression which includes immutable matrices, matrix symbols and block matrices. All functionalities of matrix expressions are also present in `BlockMatrix`.

```
>>> from sympy import (MatrixSymbol, BlockMatrix, symbols,
...     Identity, ZeroMatrix, block_collapse)
>>> n, m, l = symbols('n m l')
>>> X = MatrixSymbol('X', n, n)
>>> Y = MatrixSymbol('Y', m, m)
>>> Z = MatrixSymbol('Z', n, m)
>>> B = BlockMatrix([[X, Z], [ZeroMatrix(m,n), Y]])
>>> print(B)
Matrix([
  [X, Z],
  [0, Y]])
>>> print(B[0, 0])
X[0, 0]
```

## 4.6. Physics.

## 4.7. Series.

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

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

```
>>> from sympy import symbols, series
>>> x, y = symbols('x, y')
```

```

697 >>> series(sin(x+y) + cos(x*y), x, 0, 2)
698 1 + sin(y) + x*cos(y) + O(x**2)

```

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

706 For this, several low level methods for expansion of trigonometric, hyperbolic  
707 and other elementary functions like inverse of a series, calculating  $n$ th root, etc, are  
708 implemented using variants of the Newton[7] Method. All these support Puiseux series  
709 expansion. The following example demonstrates the use of an elementary function  
710 that calculates the Taylor expansion of the `sine` of a series.

```

711 >>> from sympy import ring
712 >>> from sympy.polys.ring_series import rs_sin
713 >>> R, x = ring('x', QQ)
714 >>> rs_sin(x**2 + x, x, 5)
715 -1/2*x**4 - 1/6*x**3 + x**2 + x

```

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

```

724 >>> from sympy.polys.ring_series import rs_series
725 >>> from sympy.abc import a, b
726 >>> from sympy import sin, cos
727 >>> rs_series(sin(a + b), a, 4)
728 -1/2*(sin(b))*a**2 + (sin(b)) - 1/6*(cos(b))*a**3 + (cos(b))*a

```

729 **4.7.2. Formal Power Series.** SymPy can be used for computing the Formal  
730 Power Series of a function. The implementation is based on the algorithm described  
731 in the paper on Formal Power Series[13]. The advantage of this approach is that an  
732 explicit formula for the coefficients of the series expansion is generated rather than  
733 just computing a few terms.

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

```

735 >>> f = fps(sin(x), x, x0=0)
736 >>> f.truncate(6)
737 x - x**3/6 + x**5/120 + O(x**6)
738 >>> f[15]
739 -x**15/1307674368000

```

740 **4.7.3. Fourier Series.** SymPy provides functionality to compute Fourier Series  
741 of a function using the `fourier_series` function. Under the hood it just computes  
742  $a_0$ ,  $a_n$ ,  $b_n$  using standard integration formulas.

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

```

744 >>> L = symbols('L')
745 >>> f = fourier_series(2 * (Heaviside(x/L) - Heaviside(x/L - 1)) - 1, (x, 0, 2*L))■

```

```

746 >>> f.truncate(3)
747 4*sin(pi*x/L)/pi + 4*sin(3*pi*x/L)/(3*pi) + 4*sin(5*pi*x/L)/(5*pi)

```

748 **4.8. Logic.** SymPy supports construction and manipulation of boolean expres-  
749 sions through the `logic` module. SymPy symbols can be used as propositional vari-  
750 ables and also be substituted as `True` or `False`. A good number of manipulation  
751 features for boolean expressions have been implemented in the `logic` module.

752 **4.8.1. Constructing boolean expressions.** A boolean variable can be de-  
753 clared as a SymPy symbol. Python operators `&`, `|` and `~` are overloaded for logical  
754 `And`, `Or` and `negate`. Several others like `Xor`, `Implies` can be constructed with `^`, `>>`  
755 respectively. The above are just a shorthand, expressions can also be constructed by  
756 directly calling `And()`, `Or()`, `Not()`, `Xor()`, `Nand()`, `Nor()`, etc.

```

757 >>> from sympy import *
758 >>> x, y, z = symbols('x y z')
759 >>> e = (x & y) | z
760 >>> e.subs({x: True, y: True, z: False})
761 True

```

762 **4.8.2. CNF and DNF.** Any boolean expression can be converted to conjunc-  
763 tive normal form, disjunctive normal form and negation normal form. The API also  
764 permits to check if a boolean expression is in any of the above mentioned forms.

```

765 >>> from sympy import *
766 >>> x, y, z = symbols('x y z')
767 >>> to_cnf((x & y) | z)
768 And(Or(x, z), Or(y, z))
769 >>> to_dnf(x & (y | z))
770 Or(And(x, y), And(x, z))
771 >>> is_cnf((x | y) & z)
772 True
773 >>> is_dnf((x & y) | z)
774 True

```

775 **4.8.3. Simplification and Equivalence.** The module supports simplification  
776 of given boolean expression by making deductions on it. Equivalence of two expres-  
777 sions can also be checked. If so, it is possible to return the mapping of variables of  
778 two expressions so as to represent the same logical behaviour.

```

779 >>> from sympy import *
780 >>> a, b, c, x, y, z = symbols('a b c x y z')
781 >>> e = a & (~a | ~b) & (a | c)
782 >>> simplify(e)
783 And(Not(b), a)
784 >>> e1 = a & (b | c)
785 >>> e2 = (x & y) | (x & z)
786 >>> bool_map(e1, e2)
787 (And(Or(b, c), a), {b: y, a: x, c: z})

```

788 **4.8.4. SAT solving.** The module also supports satisfiability checking of a given  
789 boolean expression. If satisfiable, it is possible to return a model for which the ex-  
790 pression is satisfiable. The API also supports returning all possible models. The SAT  
791 solver has a clause learning DPLL algorithm implemented with watch literal scheme  
792 and VSIDS heuristic[17].

```

793 >>> from sympy import *
794 >>> a, b, c = symbols('a b c')
795 >>> satisfiable(a & (~a | b) & (~b | c) & ~c)
796 False
797 >>> satisfiable(a & (~a | b) & (~b | c) & c)
798 {b: True, a: True, c: True}

```

SymPy includes several packages that allow users to solve domain specific problems. For example, a comprehensive physics package is included that is useful for solving problems in classical mechanics, optics, and quantum mechanics along with support for manipulating physical quantities with units.

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

---

**Listing 1** Python interpreter session showing how a vector is created using the orthogonal unit vectors of three reference frames that are oriented with respect to each other and the result of expressing the vector in the  $A$  frame. The  $B$  frame is oriented with respect to the  $A$  frame using Z-X-Z Euler Angles of magnitude  $\pi$ ,  $\frac{\pi}{2}$ , and  $\frac{\pi}{3}$  rad, respectively whereas the  $C$  frame is oriented with respect to the  $B$  frame through a simple rotation about the  $B$  frame's  $X$  unit vector through  $\frac{\pi}{2}$  rad.

---

```

>>> from sympy import pi
>>> from sympy.physics.vector import ReferenceFrame
>>> A = ReferenceFrame('A')
>>> B = ReferenceFrame('B')
>>> C = ReferenceFrame('C')
>>> B.orient(A, 'body', (pi, pi / 3, pi / 4), 'zxz')
>>> C.orient(B, 'axis', (pi / 2, B.x))
>>> v = 1 * A.x + 2 * B.z + 3 * C.y
>>> v
A.x + 2*B.z + 3*C.y
>>> v.express(A)
A.x + 5*sqrt(3)/2*A.y + 5/2*A.z

```

---

**4.10. Classical Mechanics.** The `physics.mechanics` package utilizes the `physics.vector` package to populate time aware particle and rigid body objects to fully describe the kinematics and kinetics of a rigid multi-body system. These objects store all of the information needed to derive the ordinary differential or differential algebraic equations that govern the motion of the system, i.e., the equations of motion. These equations of motion abide by Newton's laws of motion and can handle any arbitrary kinematical constraints or complex loads. The package offers two automated methods for formulating the equations of motion based on Lagrangian Dynamics [16] and

Kane’s Method [15]. Lastly, there are automated linearization routines for constrained dynamical systems based on [19].

**4.11. Quantum Mechanics.** The `sympy.physics.quantum` package provides quantum functions, states, operators, and computation of standard quantum models.

**4.12. Optics.** The `physics.optics` package provides Gaussian optics functions.

**4.13. Units.** The `physics.units` module provides around two hundred predefined prefixes and SI units that are commonly used in the sciences. Additionally, it provides the `Unit` class which allows the user to define their own units. These prefixes and units are multiplied by standard SymPy objects to make expressions unit aware, allowing for algebraic and calculus manipulations to be applied to the expressions while the units are tracked in the manipulations. The units of the expressions can be easily converted to other desired units. There is also a new units system in `sympy.physics.unitsystems` that allows the user to work in specified unit systems.

**5. 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.
- **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.
- **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.

**5.1. 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 1:

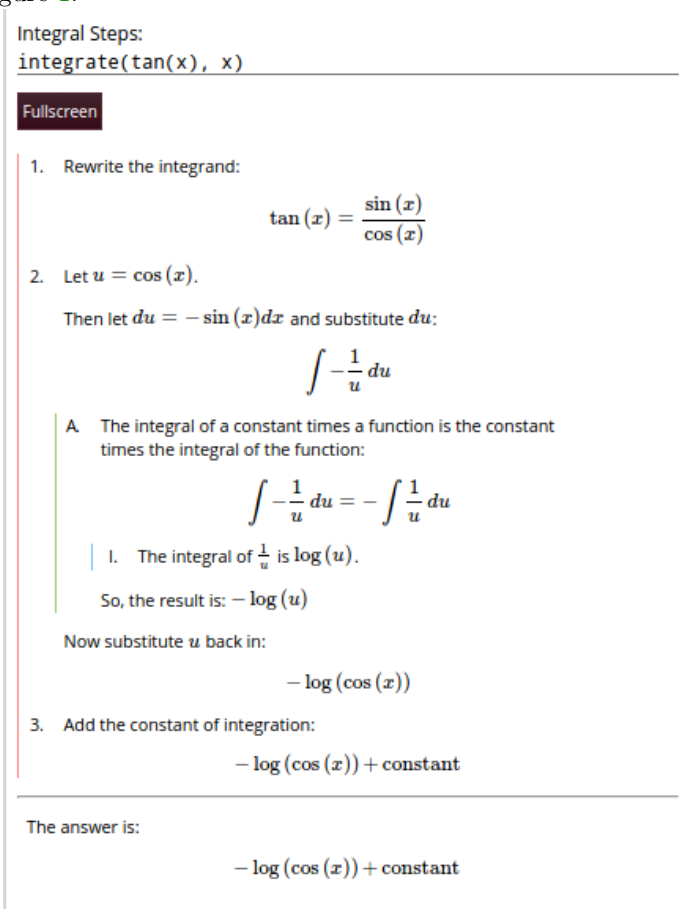


Fig. 1: Integral steps of  $\tan(x)$

- 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.

**5.2. 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.

## 6. Comparison with other CAS.

**6.1. Mathematica.** Wolfram Mathematica is a popular proprietary CAS. It features highly advanced algorithms. Mathematica has a core implemented in C++ [2] 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.

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.

## 7. Conclusion and future work.

## 8. References.

### REFERENCES



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