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# Keras

https://keras-cn.readthedocs.io/en/latest/

Keras的核心数据结构是“模型”,Keras的底层库使用Theano或TensorFlow(“符号主义”的库)

与传统的Python代码区别？

符号主义的计算首先定义各种变量，然后建立“计算图”，计算图规定了各个变量之间的计算关系。建立好的计算图需要编译已确定其内部细节，然而，此时的计算图还是一个“空壳子”，里面没有任何实际的数据，只有当你把需要运算的输入放进去后，才能在整个模型中形成数据流，从而形成输出值

深度学习的优化算法，说白了就是梯度下降。每次的参数更新有两种方式：

Batch gradient descent（批梯度下降）：遍历全部数据集算一次损失函数，然后算函数对各个参数的梯度，更新梯度。缺点：计算量开销大，计算速度慢，不支持在线学习

stochastic gradient descent（随机梯度下降）：速度快，但收敛性不好，可能在最优点附近晃来晃去，hit不到最优点。两次参数的更新也有可能互相抵消掉，造成目标函数震荡的比较剧烈

mini-batch gradient decent（小批的梯度下降）：数据分为若干批，按批来更新参数，批中的一组数据共同决定了本次梯度的方向，下降起来就不容易跑偏，减少了随机性

张量可以看作是向量、矩阵的自然推广，我们用张量来表示广泛的数据类型

0阶张量，即标量，也就是一个数

1阶张量，也就是一个向量

2阶张量，也就是一个矩阵

3阶张量，一个立方体

张量的阶数有时候也称为维度，或者轴

Ubuntu 16.04 LTS是Nvidia官方以及绝大多数深度学习框架默认开发环境

Theano: a compiler for mathematical expressions in Python

TensorFlow: a python library for fast numerical computing

Keras: library addresses these concerns by providing a wrapper for both Theano and Tensorflow

scikit-learn library：general purpose machine learning framework in Python built on top

of SciPy

application checkpointing

dropout

convolutional neural networks

## 安装

# 系统升级

$ sudo apt update

$ sudo apt upgrade

# 安装python基础开发包

$ sudo apt install -y python-dev python-pip python-nose gcc g++ git gfortran vim

# 安装运算加速库

$ sudo apt install -y libopenblas-dev liblapack-dev libatlas-base-dev

# 安装CUDA开发环境

$ sudo dpkg -i cuda-repo-ubuntu1604-8-0-local\_8.0.44-1\_amd64.deb

$ sudo apt update

$ sudo apt install cuda

# 将CUDA路径添加至环境变量

$ sudo gedit /etc/bash.bashrc

在bash.bashrc文件中添加：

export CUDA\_HOME=/usr/local/cuda-8.0

export PATH=/usr/local/cuda-8.0/bin${PATH:+:${PATH}}

export LD\_LIBRARY\_PATH=/usr/local/cuda-8.0/lib64${LD\_LIBRARY\_PATH:+:${LD\_LIBRARY\_PATH}}

$ source gedit /etc/.bashrc

在.bashrc中添加如上相同内容

$ sudo gedit ~/.bashrc

$ nvcc -v 测试nVidia cuda版本号

Keras框架搭建

$ sudo pip install -U --pre pip setuptools wheel

$ sudo pip install -U --pre numpy scipy matplotlib scikit-learn scikit-image

$ sudo pip install -U --pre theano

$ sudo pip install -U --pre keras

注：依赖numpy，scipy, pyyaml, HDF5, h5py（可选，仅在模型的save/load函数中使用）

TensorFlow(当使用TensorFlow为后端时) or Theano(当使用Theano作为后端时), Keras默认使用TensorFlow作为后端来进行张量操作

keras$ sudo python setup.py install

or $ sudo pip install keras

$ python 验证

>>> import theano

>>> import keras

Keras环境设置

修改默认keras后端: gedit ~/.keras/keras.json

配置theano文件: gedit ~/.theanorc

[global]

openmp=False

device = gpu

floatX = float32

allow\_input\_downcast=True

[lib]

cnmem = 0.8

[blas]

ldflags= -lopenblas

[nvcc]

fastmath = True

验证keras是否安装成功

>>>import keras

加速测试

keras/examples/$ python mnist\_mlp.py

## workflow

Load Data.

Define Model.

Compile Model.

Fit Model.

Evaluate Model.

Tie It All Together.

# Scipy

<http://www.scipy.org/install.html>

## install

Upgrade pip

$ python -m pip install --upgrade pip

$ pip install --user numpy scipy matplotlib ipython jupyter pandas sympy nose

# user install executable directory is on your PATH

# Consider adding this at the end of your ~/.bashrc file

export PATH="$PATH:/home/your\_user/.local/bin"

## NumPy

<http://old.sebug.net/paper/books/scipydoc/numpy_intro.html>

NumPy提供了两种基本的对象：ndarray（N-dimensional array object）和 ufunc（universal function object）

创建

# 通过给array函数传递Python的序列对象创建数组，如果传递的是多层嵌套的序列，将创建多维数组

>>> a = np.array([1, 2, 3, 4])

>>> b = np.array((5, 6, 7, 8), dtype=np.float)

>>> c = np.array([[1, 2, 3, 4],[4, 5, 6, 7], [7, 8, 9, 10]], dtype=np.complex)

c.dtype 数组元素类型

c.shape 数组尺寸

c.shape = 4,3 #原数组尺寸改变

d = a.reshape((2, 2)) #原数组尺寸不改变，但生成指定尺寸的新数组，注意a and d共享数据存储内存区域

np.arange(0, 1, 0.1) #类似python的range，指定开始值，终值和步长，注意不包括终值

np.linspace(0, 1, 12) #等差数列，包括终值

np.logspace(0, 2, 20) #等比数列

np.fromstring("abcdefgh", dtype=np.int8)

# 用C语言的二进制方式写了一组double类型的数值到某个文件中，那们可以从此文件读取相应的数据，并通过fromstring函数将其转换为float64类型的数组

def func(i):

return i%4+1

np.fromfunction(func, (10,)) #第一个参数为计算每个元素的函数，第二个参数为数组大小

存取元素

a[5]

a[3:5] #通过下标范围获取的新的数组是原始数组的一个视图。它与原始数组共享同一块数据空间

a[:5]

a[:-1]

a[1:-1:2] 第三个参数表示步长

a[::-1] 数组逆序

a[[3, 3, 1, 8]] 使用整数序列作为下标获得的数组不和原始数组共享数据空间

a[a>5] 使用布尔数组作为下标获得的数组不和原始数组共享数据空间

多维数组

NumPy采用组元(tuple)作为数组的下标

也有整数序列或布尔数组作为下标，注意是多维

内存结构



ufunc运算： 对数组的每个元素进行操作的函数

result = np.sin(a)

result = a1 + a2 类似matlab点运算

+, -, \*, /, //, \*\*, %

广播

# array([[ 0],

[10],

[20],

[30],

[40],

[50]])

a = np.arange(0, 60, 10).reshape(-1, 1)

# array([0, 1, 2, 3, 4])

b = np.arange(0, 5)

c = a + b

array([[ 0, 1, 2, 3, 4],

[10, 11, 12, 13, 14],

[20, 21, 22, 23, 24],

[30, 31, 32, 33, 34],

[40, 41, 42, 43, 44],

[50, 51, 52, 53, 54]])

x, y = np.ogrid[0:1:4j, 0:1:3j] 开始值：结束值： 数组长度

x =

array([[ 0. ],

[ 0.33333333],

[ 0.66666667],

[ 1. ]])

y = array([[ 0. , 0.5, 1. ]])

利用ogrid的返回值，我能很容易计算x, y网格面上各点的值，或者x, y, z网格体上各点的值

x, y = np.ogrid[-2:2:20j, -2:2:20j]

z = x \* np.exp( - x\*\*2 - y\*\*2)

文件存取

numpy.load和numpy.save函数以NumPy专用的二进制类型保存数据，这两个函数会自动处理元素类型和shape等信息

>>> np.save("a.npy", a)

>>> c = np.load( "a.npy" )

将多个数组保存到一个文件中的话，可以使用numpy.savez函数

np.savez("result.npz", a, b, sin\_array = c)

>>> r = np.load("result.npz")

## scipy

SciPy contains additional routines needed in scientific work: for example, routines for computing integrals numerically, solving differential equations, optimization, and sparse matrices.

Subpackage Description

cluster Clustering algorithms

constants Physical and mathematical constants

fftpack Fast Fourier Transform routines

integrate Integration and ordinary differential equation solvers

interpolate Interpolation and smoothing splines

io Input and Output

linalg Linear algebra

ndimage N-dimensional image processing

odr Orthogonal distance regression

optimize Optimization and root-finding routines

signal Signal processing

sparse Sparse matrices and associated routines

spatial Spatial data structures and algorithms

special Special functions

stats Statistical distributions and functions

weave C/C++ integration

<https://docs.scipy.org/doc/scipy/reference/tutorial/basic.html>

>>> import numpy as np

>>> import matplotlib as mpl

>>> import matplotlib.pyplot as plt

>>> from scipy import linalg, optimize

a = np.r\_[3,[0]\*5,-1:1:10j] row concatenation

np.c\_ column concatenation

meshgrid

produce N, N-d arrays which provide coordinate arrays for an N-dimensional volume

>>> np.mgrid[0:5:4j,0:5:4j]

array([[[ 0. , 0. , 0. , 0. ],

[ 1.6667, 1.6667, 1.6667, 1.6667],

[ 3.3333, 3.3333, 3.3333, 3.3333],

[ 5. , 5. , 5. , 5. ]],

[[ 0. , 1.6667, 3.3333, 5. ],

[ 0. , 1.6667, 3.3333, 5. ],

[ 0. , 1.6667, 3.3333, 5. ],

[ 0. , 1.6667, 3.3333, 5. ]]])

Polynomials

1-d polynomials = poly1d class (coefficients or polynomial roots to initialize a po lynomial)

manipulated in algebraic expressions, integrated, differentiated, and evaluated

>>> from numpy import poly1d

>>> p = poly1d([3,4,5]) 3x\*x + 4x + 5

>>> print p.integ(k=6) 积分

>>> print p.deriv() 微分

Vectorizing functions (vectorize)

# 定义标量函数

>>> def addsubtract(a,b):

... if a > b:

... return a - b

... else:

... return a + b

# 矢量化标量函数

>>> vec\_addsubtract = np.vectorize(addsubtract)

>>> vec\_addsubtract([0,3,6,9],[1,3,5,7])

Special functions (scipy.special)

airy, elliptic, bessel, gamma, beta, hypergeometric, parabolic cylinder, mathieu, spheroidal wave, struve, and kelvin

>>> from scipy import special

>>> def drumhead\_height(n, k, distance, angle, t):

... kth\_zero = special.jn\_zeros(n, k)[-1]

... return np.cos(t) \* np.cos(n\*angle) \* special.jn(n, distance\*kth\_zero)

>>> theta = np.r\_[0:2\*np.pi:50j]

>>> radius = np.r\_[0:1:50j]

>>> x = np.array([r \* np.cos(theta) for r in radius])

>>> y = np.array([r \* np.sin(theta) for r in radius])

>>> z = np.array([drumhead\_height(1, 1, r, theta, 0.5) for r in radius])

Integration (scipy.integrate)

>>> help(integrate)

>>> from scipy.integrate import quad 单变量积分

>>> from scipy.integrate import dblquad 双变量积分

>>> from scipy.integrate import tplquad 三变量积分

>>> from scipy.integrate import nquad 多变量积分

>>> N = 5

>>> def f(t, x):

... return np.exp(-x\*t) / t\*\*N

>>> nquad(f, [[1, np.inf],[0, np.inf]])

>>> from scipy.integrate import simps Integrating using Samples

Ordinary differential equations 常微分方程

>>> from scipy.integrate import odeint

Optimization (scipy.optimize)

1. Unconstrained and constrained minimization of multivariate scalar functions (minimize) using a variety of algorithms (e.g. BFGS, Nelder-Mead simplex, Newton Conjugate Gradient, COBYLA or SLSQP)

2. Global (brute-force) optimization routines (e.g. basinhopping, differential\_evolution)

3. Least-squares minimization (least\_squares) and curve fitting (curve\_fit) algorithms

4. Scalar univariate functions minimizers (minimize\_scalar) and root finders (newton)

5. Multivariate equation system solvers (root) using a variety of algorithms (e.g. hybrid Powell, Levenberg-Marquardt or large-scale methods such as Newton-Krylov).

>>> from scipy.optimize import minimize

# Unconstrained minimization of multivariate scalar functions 无约束

>>> def rosen(x):

... """The Rosenbrock function"""

... return sum(100.0\*(x[1:]-x[:-1]\*\*2.0)\*\*2.0 + (1-x[:-1])\*\*2.0)

>>> x0 = np.array([1.3, 0.7, 0.8, 1.9, 1.2])

>>> res = minimize(rosen, x0, method='nelder-mead',

... options={'xtol': 1e-8, 'disp': True})

# Constrained minimization of multivariate scalar functions (minimize) 有约束

the Sequential Least SQuares Programming optimization algorithm (SLSQP)

Least-squares minimization (least\_squares)

Univariate function minimizers (minimize\_scalar)

# Unconstrained minimization (method='brent')

>>> from scipy.optimize import minimize\_scalar

>>> f = lambda x: (x - 2) \* (x + 1)\*\*2

>>> res = minimize\_scalar(f, method='brent')

# Bounded minimization (method='bounded')

>>> from scipy.special import j1

>>> res = minimize\_scalar(j1, bounds=(4, 7), method='bounded')

Root finding

# Finding a root of a set of non-linear equations can be achieve using the root function

>>> import numpy as np

>>> from scipy.optimize import root

>>> def func(x):

... return x + 2 \* np.cos(x)

>>> sol = root(func, 0.3)

Interpolation (scipy.interpolate)

# 1-D interpolation (interp1d)

>>> from scipy.interpolate import interp1d

>>> x = np.linspace(0, 10, num=11, endpoint=True)

>>> y = np.cos(-x\*\*2/9.0)

>>> f = interp1d(x, y)

>>> f2 = interp1d(x, y, kind='cubic')

# Multivariate data interpolation (griddata)

>>> from scipy.interpolate import griddata

>>> points = np.random.rand(1000, 2)

>>> values = func(points[:,0], points[:,1])

>>> grid\_x, grid\_y = np.mgrid[0:1:100j, 0:1:200j]

>>> grid\_z0 = griddata(points, values, (grid\_x, grid\_y), method='nearest')

>>> grid\_z1 = griddata(points, values, (grid\_x, grid\_y), method='linear')

>>> grid\_z2 = griddata(points, values, (grid\_x, grid\_y), method='cubic')

# Spline interpolation in 1-d: Procedural (interpolate.splXXX)

Spline interpolation requires two essential steps: (1) a spline representation of the curve is computed, and (2) the spline is evaluated at the desired points. In order to find the spline representation, there are two different ways to represent a curve and obtain (smoothing) spline coefficients: directly and parametrically

>>> from scipy.interpolate import splrep， splev

>>> x = np.arange(0, 2\*np.pi+np.pi/4, 2\*np.pi/8)

>>> y = np.sin(x)

>>> tck = splrep(x, y, s=0)

>>> xnew = np.arange(0, 2\*np.pi, np.pi/50)

>>> ynew = splev(xnew, tck, der=0)

Two-dimensional spline representation: Procedural (bisplrep)

>>> from scipy.interpolate import bisplrep, bisplev

>>> x, y = np.mgrid[-1:1:20j, -1:1:20j]

>>> z = (x+y) \* np.exp(-6.0\*(x\*x+y\*y))

>>> xnew, ynew = np.mgrid[-1:1:70j, -1:1:70j]

>>> tck = interpolate.bisplrep(x, y, z, s=0)

>>> znew = interpolate.bisplev(xnew[:,0], ynew[0,:], tck)

Fourier analysis

discrete Fourier transform (DFT)

Fast Fourier Transform (FFT)

>>> from scipy.fftpack import fft, ifft

>>> x = np.array([1.0, 2.0, 1.0, -1.0, 1.5])

>>> y = fft(x)

>>> yinv = ifft(y)

Two and n-dimensional discrete Fourier transforms

>>> from scipy.fftpack import fft2, ifft2, fftn, ifftn

Discrete Cosine Transforms

>>> from scipy.fftpack import dct, idct

Discrete Sine Transforms

>>> from scipy.fftpack import dst, idst

Signal Processing (scipy.signal)

Filtering: Convolution/Correlation

Time-discrete filters: FIR(finite response filters) and IIR(infinite response filters)

Other filters: Median Filter, Order Filter, Wiener filter, Hilbert filter

Spectral Analysis, spectral density

Analog Filter Design

Linear Algebra (scipy.linalg)

scipy.linalg vs numpy.linalg

numpy.matrix vs 2D numpy.ndarray

Basic routines: Inverse, Solving linear system, Determinant, norms, Solving linear least-squares problems and pseudo-inverses, Decompositions(Eigenvalues and eigenvectors), SVD(Singular value decomposition)

Singular Value Decomposition (SVD) can be thought of as an extension of the eigenvalue problem to matrices that are not square, Every matrix has a singular value decomposition. Sometimes, the singular values are called the spectrum of A

Sparse Eigenvalue Problems with ARPACK

Spatial data structures and algorithms (scipy.spatial)

Delaunay triangulations

The Delaunay triangulation is a subdivision of a set of points into a non-overlapping set of triangles,

Convex hulls

Convex hull is the smallest convex object containing all points in a given point set.

Voronoi diagrams

A Voronoi diagram is a subdivision of the space into the nearest neighborhoods of a given set of points.

Statistics (scipy.stats)

continuous random variables and discrete random variables . Over 80 continuous random variables (RVs) and 10 discrete random variables

The main public methods for continuous RVs are:

rvs: Random Variates

pdf: Probability Density Function

cdf: Cumulative Distribution Function

sf: Survival Function (1-CDF)

ppf: Percent Point Function (Inverse of CDF)

isf: Inverse Survival Function (Inverse of SF)

stats: Return mean, variance, (Fisher’s) skew, or (Fisher’s) kurtosis

moment: non-central moments of the distribution

Multidimensional image processing (scipy.ndimage)

Correlation and convolution

Fourier domain filters

Distance transforms

Interpolation functions

Morphology: Binary morphology, Grey-scale morphology

Segmentation and labeling

Object measurements

File IO (scipy.io)

MATLAB files

>>> import scipy.io as sio

sio.loadmat(file\_name[, mdict, appendmat]) Load MATLAB file.

sio.savemat(file\_name, mdict[, appendmat, ...]) Save a dictionary of names and arrays into a MATLAB-style .mat file.

sio.whosmat(file\_name[, appendmat]) List variables inside a MATLAB file.

Weave (scipy.weave)

The scipy.weave (below just weave) package provides tools for including C/C++ code within in Python code

## matplotlib

import matplotlib.pyplot as plt

plt.plot([1,2,3,4]) # array of y-axis, the default x [0, .. len(y)-1]

or plt.plot(t, t, 'r--', t, t\*\*2, 'bs', t, t\*\*3, 'g^')

plt.ylabel('some numbers')

plt.show()

Controlling line properties （matplotlib.lines.Line2D）

linewidth, dash style, antialiased, ...

same to matlab, pyplot has concept of current figure and axes

matplotlib.axes.Axes = gca()

matplotlib.figure.Figure = gcf()

clf(), cla(), close()

xlabel(), ylabel(), title() , text(), annotate(), xscale(‘log’), yscale9'log')

import numpy as np

import matplotlib.pyplot as plt

def f(t):

return np.exp(-t) \* np.cos(2\*np.pi\*t)

t1 = np.arange(0.0, 5.0, 0.1)

t2 = np.arange(0.0, 5.0, 0.02)

plt.figure(1)

plt.subplot(211)

plt.plot(t1, f(t1), 'bo', t2, f(t2), 'k')

plt.subplot(212)

plt.plot(t2, np.cos(2\*np.pi\*t2), 'r--')

plt.show()

TeX markup in any matplotlib text

<http://matplotlib.org/users/mathtext.html>

## pandas

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

dates = pd.date\_range('20130101', periods=6)

df = pd.DataFrame(np.random.randn(6,4), index=dates, columns=list('ABCD'))

df.head()

df.tail(3)

df.index

df.columns

df.values

df.T

df.sort\_index(axis=1, ascending=False) #sorting by an axis

df.sort\_values(by='B') #sorting by values

selection

df['A'] # select a single column

df.loc['20130102':'20130104',['A','B']] # both endpoints are included

df.at[dates[0],'A'] # 获取单元素

df[0:3] # slices the rows.

df.iloc[3:5,0:2] # By integer slices

df.iat[1,1] # 获取单元素

Boolean Indexing

df[df.A > 0]

df[df > 0]

df2[df2['E'].isin(['two','four'])]

df2[df2 > 0] = -df2 #只对df2>0的部分进行操作，别的元素不动

Missing Data

pandas primarily uses the value np.nan to represent missing data. It is by default not included in computations

df1.dropna(how='any') # To drop any rows that have missing data.

df1.fillna(value=5) # Filling missing data

pd.isnull(df1) # To get the boolean mask where values are nan

df.describe() # 描述性统计

df.apply(lambda x: x.max() - x.min()) # 列处理

s = pd.Series(np.random.randint(0, 7, size=10))

s.value\_counts() # 直方图

pd.concat([df[:3], df[3:7], df[7:]])

pd.merge(left, right, on='key') # SQL style merges

df.append(s, ignore\_index=True) # Append rows to a dataframe

Grouping：

Splitting the data into groups based on some criteria

Applying a function to each group independently

Combining the results into a data structure

df.groupby('A').sum()

Time Series

Converting between period and timestamp

rng = pd.date\_range('3/6/2012 00:00', periods=5, freq='D')

rng = pd.date\_range('1/1/2012', periods=5, freq='M')

Categoricals

df = pd.DataFrame({"id":[1,2,3,4,5,6], "raw\_grade":['a', 'b', 'b', 'a', 'a', 'e']})

df["grade"] = df["raw\_grade"].astype("category")

df.to\_csv('foo.csv') # Writing to a csv file

pd.read\_csv('foo.csv') # Reading from a csv file

df.to\_hdf('foo.h5','df') # Writing to a HDF5 Store

pd.read\_hdf('foo.h5','df') # Reading from a HDF5 Store

df.to\_excel('foo.xlsx', sheet\_name='Sheet1') # Writing to an excel file

pd.read\_excel('foo.xlsx', 'Sheet1', index\_col=None, na\_values=['NA']) # Reading from an excel file

## SymPy

Symbolic computation deals with the computation of mathematical objects symbolically

Symbolic computation systems (which by the way, are also often called computer algebra systems, or just CASs) such as SymPy are capable of computing symbolic expressions with variables.

SymPy can simplify expressions, compute derivatives, integrals, and limits, solve equations, work with matrices, it includes modules for plotting, printing (like 2D pretty printed output of math formulas, or LATEXLATEX), code generation, physics, statistics, combinatorics, number theory, geometry, logic, and more

Whenever you combine a SymPy object and a SymPy object, or a SymPy object and a Python object, you get a SymPy object, but whenever you combine two Python objects, SymPy never comes into play, and so you get a Python object.

import math

math.sqrt(8)

import sympy

sympy.sqrt(8)

易犯错误点：

x = symbols('x')

expr = x + 1

expr.subs(x, 2) 符号表达式求值

expr.subs(x, x\*y) 符号替换

expr = x\*\*3 + t\*x\*y - z

expr.subs([(x, 2), (y, 4), (z, 0)])

expr = x\*\*4 - 4\*x\*\*3 + 4\*x\*\*2 - 2\*x + 3

replacements = [(x\*\*i, y\*\*i) for i in range(5) if i%2 == 0]

expr.subs(replacements) 结果y\*\*4 - 4\*x\*\*3 + 4\*y\*\*2 - 2\*x + 3

注意：SymPy expressions are immutable, no function will change them in-place. All functions will return new expressions.

条件测试

a = (x+1)\*\*2

b = x\*\*2 + 2\*x + 1

if simplify(a - b) == 0:

if a.equals(b):

字符串转符号表达式converting strings to sympy expressions

str\_expr = "x\*\*2 + 3\*x - 1/2"

expr = sympify(str\_expr)

convert a SymPy expression to an expression

expr = sin(x)

f = lambdify(x, expr, "numpy")

f(numpy.arange(10))

Simplification

uses heuristics to determine the simplest result

>>> simplify(sin(x)\*\*2 + cos(x)\*\*2)

>>> simplify((x\*\*3 + x\*\*2 - x - 1)/(x\*\*2 + 2\*x + 1))

Polynomial/Rational Function Simplification

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

>>> expand((x + 1)\*\*2)

>>> factor(x\*\*2\*z + 4\*x\*y\*z + 4\*y\*\*2\*z)

expr.coeff(x, n) gives the coefficient of x\*\*n in expr:

>>> expr = x\*y + x - 3 + 2\*x\*\*2 - z\*x\*\*2 + x\*\*3

>>> collected\_expr = collect(expr, x)

>>> collected\_expr.coeff(x, 2)

>>> trigsimp(sin(x)\*tan(x)/sec(x)) #simplify trigonometric

>>> expand\_trig(sin(x + y)) #expand trigonometric functions

By default, SymPy Symbols are assumed to be complex

Symbols can be given different assumptions by passing the assumption to symbols()

>>> x, y = symbols('x y', positive=True)

>>> a, b = symbols('a b', real=True)

Special Functions

>>> factorial(n)

>>> binomial(n, k) n choose k

>>> gamma(z)

Calculus

>>> diff(x\*\*4, x, 3) #the third derivative 微分

>>> diff(exp(x\*y\*z), x, y, 2, z, 4) #多阶偏微分

integrate(exp(x)\*sin(x) + exp(x)\*cos(x), x) 积分

integrate(sin(x\*\*2), (x, -oo, oo)) 定积分

>>> integrate(exp(-x\*\*2 - y\*\*2), (x, -oo, oo), (y, -oo, oo)) #多变量积分

limit(sin(x)/x, x, 0) 极限

>>> limit(1/x, x, 0, '+') 单边极限

>>> expr = exp(sin(x))

>>> expr.series(x, 0, 4) 泰勒级数展开

Solvers

Eq(x+1, 4) x+1 = 4 方程等式

>>> solveset(Eq(x\*\*2, 1), x) #solving algebraic equations

注：solve(x\*\*2 - 2, x)求根不被推荐

>>> f = symbols('f', cls=Function)

>>> diffeq = Eq(f(x).diff(x, x) - 2\*f(x).diff(x) + f(x), sin(x))

>>> dsolve(diffeq, f(x)) 解微分方程

Matrix([[1, 2], [2, 2]]).eigenvals()

besselj(nu, z).rewrite(jn)

latex(Integral(cos(x)\*\*2, (x, 0, pi)))