

# Documentation

This version of the document is dated 2020-08-14.

Help on module randomgen:

NAME

randomgen

DESCRIPTION

Sample code for the article "Randomization and Sampling Methods"

[<https://www.codeproject.com/Articles/1190459/Random-Number-Generation-Methods>]

(<https://www.codeproject.com/Articles/1190459/Random-Number-Generation-Methods>)

Written by Peter O.

Any copyright is released to the Public Domain.

[<https://creativecommons.org/publicdomain/zero/1.0/>]

(<https://creativecommons.org/publicdomain/zero/1.0/>)

CLASSES

builtins.object

AlmostRandom

BinaryExpansion

BringmannLarsen

ConvexPolygonSampler

DensityInversionSampler

DensityTiling

FastLoadedDiceRoller

KVectorSampler

OptimalSampler

PascalTriangle

RandomGen

RatioOfUniformsTiling

SortedAliasMethod

VoseAlias

class AlmostRandom(builtins.object)

| Methods defined here:

| \_\_init\_\_(self, randgen, list)

| Initialize self. See help(type(self)) for accurate signature.

| choose(self)

| Data descriptors defined here:

| \_\_dict\_\_

| dictionary for instance variables (if defined)

| \_\_weakref\_\_

| list of weak references to the object (if defined)

class BinaryExpansion(builtins.object)

| Methods defined here:

| \_\_init\_\_(self, arr, zerosAtEnd=False)

| Binary expansion of a real number in [0, 1], initialized  
| from an array of zeros and ones expressing the binary  
| expansion.

| The first binary digit is the half digit, the second  
| is the quarter digit, the third is the one-eighth digit,

and so on. Note that the number 1 can be expressed by passing an empty array and specifying `zerosAtEnd = False`, and the number 0 can be expressed by passing an empty array and specifying `zerosAtEnd = True`.  
`arr` - Array indicating the initial digits of the binary expansion.  
`zerosAtEnd` - Indicates whether the binary expansion is expressed as `0.xxx0000...` or `0.yyy1111...` (e.g., `0.1010000...` vs. `0.1001111...`. Default is the latter case (`False`).

`entropy(self)`

`eof(self)`

Returns True if the end of the binary expansion was reached; False otherwise.

`fromFloat(f)`

Creates a binary expansion object from a 64-bit floating-point number in the interval `[0, 1]`.

`fromFraction(f)`

Creates a binary expansion object from a fraction in the interval `[0, 1]`.

`get(f)`

Creates a binary expansion object from a fraction, 'int', or 'float' in the interval `[0, 1]`; returns 'f' unchanged, otherwise.

`getOrReset(f)`

Creates a binary expansion object from a fraction, 'int', or 'float' in the interval `[0, 1]`; resets 'f' (calls its reset method) otherwise.

`nextbit(self)`

Reads the next bit in the binary expansion.

`reset(self)`

Resets this object to the first bit in the binary expansion.

`value(self)`

-----  
 Data descriptors defined here:

`__dict__`

dictionary for instance variables (if defined)

`__weakref__`

list of weak references to the object (if defined)

`class BringmannLarsen(builtins.object)`

Implements Bringmann and Larsen's sampler, which chooses a random number in `[0, n)` where the probability that each number is chosen is weighted. The 'weights' is the list of weights each 0 or greater; the higher the weight, the greater the probability. This sampler supports only integer weights. This is a succinct (space-saving) data structure for this purpose.

Reference:

K. Bringmann and K. G. Larsen, "Succinct Sampling from Discrete Distributions", In: Proc. 45th Annual ACM Symposium on Theory of Computing (STOC'13), 2013.

Methods defined here:

```

|   __init__(self, weights)
|       Initialize self. See help(type(self)) for accurate signature.
|
|   next(self, randgen)
|
|   -----
|   Data descriptors defined here:
|
|   __dict__
|       dictionary for instance variables (if defined)
|
|   __weakref__
|       list of weak references to the object (if defined)
|
class ConvexPolygonSampler(builtins.object)
|   A class for uniform random sampling of
|   points from a convex polygon. This
|   class only supports convex polygons because
|   the random sampling process involves
|   triangulating a polygon, which is trivial
|   for convex polygons only. "randgen" is a RandomGen
|   object, and "points" is a list of points
|   (two-item lists) that make up the polygon.
|
|   Methods defined here:
|
|   __init__(self, randgen, points)
|       Initialize self. See help(type(self)) for accurate signature.
|
|   sample(self)
|       Choose a random point in the convex polygon
|       uniformly at random.
|
|   -----
|   Data descriptors defined here:
|
|   __dict__
|       dictionary for instance variables (if defined)
|
|   __weakref__
|       list of weak references to the object (if defined)
|
class DensityInversionSampler(builtins.object)
|   A sampler that generates random samples from
|   a continuous distribution for which
|   only the probability density function (PDF) is known,
|   using the inversion method. This sampler
|   allows quantiles for the distribution to be calculated
|   from pregenerated uniform random numbers in [0, 1].
|
|   - pdf: A function that specifies the PDF. It takes a single
|   number and outputs a single number. The area under
|   the PDF need not equal 1 (this sampler works even if the
|   PDF is only known up to a normalizing constant).
|   - bl, br - Specifies the sampling domain of the PDF. Both
|   bl and br are numbers giving the domain,
|   which in this case is [bl, br]. For best results, the
|   probabilities outside the sampling domain should be
|   negligible (the reference cited below uses cutoff points
|   such that the probabilities for each tail integrate to
|   about ures*0.05 or less).

```

```

- ures - Maximum approximation error tolerable, or
  "u-resolution". Default is 10^-8. This error tolerance
  "does not work for continuous distributions [whose PDFs
  have] high and narrow peaks or poles".

Reference:
Gerhard Derflinger, Wolfgang Hörmann, and Josef Leydold,
"Random variate generation by numerical inversion when
only the density is known", ACM Transactions on Modeling
and Computer Simulation 20(4) article 18, October 2010.

Methods defined here:

__init__(self, pdf, bl, br, ures=1e-08)
    Initialize self. See help(type(self)) for accurate signature.

codegen(self, name='dist')
    Generates standalone Python code that samples
    (approximately) from the distribution estimated
    in this class. Idea from Leydold, et al.,
    "An Automatic Code Generator for
    Nonuniform Random Variate Generation", 2001.
    - name: Distribution name. Generates Python methods called
      sample_X (samples one random number), and quantile_X
      (finds the quantile
      for a uniform random number in [0, 1]),
      where X is the name given here.

quantile(self, v)
    Calculates quantiles from uniform random numbers
    in the interval [0, 1].
    - v: A list of uniform random numbers.
    Returns a list of the quantiles corresponding to the
    uniform random numbers. The returned list will have
    the same number of entries as 'v'.

sample(self, rg, n=1)
    Generates random numbers that (approximately) follow the
    distribution modeled by this class.
    - n: The number of random numbers to generate.
    Returns a list of 'n' random numbers.

-----
Data descriptors defined here:

__dict__
    dictionary for instance variables (if defined)

__weakref__
    list of weak references to the object (if defined)

class DensityTiling(builtins.object)
    Produces a tiling of a probability density function (PDF)
    for the purposes of random number generation. The PDF is
    decomposed into tiles; these tiles will either cross the PDF
    or go below the PDF. In each recursion cycle, each tile is
    split into four tiles, and tiles that end up above the PDF are
    discarded.

    - pdf: A function that specifies the PDF. It takes a single
      number and outputs a single number. The area under
      the PDF need not equal 1 (this class tolerates the PDF even if

```

```

| it is only known up to a normalizing constant). For best results,
| the PDF should be bounded from above (that is, it should be free of _poles_, or
points | that approach infinity). If the PDF does contain a pole, this class
| may accommodate the pole by sampling from a modified version of the PDF,
| so that points extremely close to the pole may be sampled
| at a higher or lower probability than otherwise (but not in a way
| that significantly affects the chance of sampling points
| outside the pole region).
| - bl, br - Specifies the sampling domain of the PDF. Both
|   bl and br are numbers giving the domain,
|   which in this case is [bl, br].
| - cycles - Number of recursion cycles in which to split tiles
|   that follow the PDF. Default is 8.
|
| Additional improvements not yet implemented: Hörmann et al.,
| "Inverse Transformed Density Rejection for Unbounded Monotone Densities", 2007.
|
| Reference:
| Fulger, Daniel and Guido Germano. "Automatic generation of
| non-uniform random variates for arbitrary pointwise computable
| probability densities by tiling",
| arXiv:0902.3088v1 [cs.MS], 2009.
|
| Methods defined here:
|
| __init__(self, pdf, bl, br, cycles=8)
|     Initialize self. See help(type(self)) for accurate signature.
|
| codegen(self, name, pdfcall=None)
|     Generates Python code that samples
|         (approximately) from the distribution estimated
|         in this class. Idea from Leydold, et al.,
|         "An Automatic Code Generator for
|         Nonuniform Random Variate Generation", 2001.
|     - name: Distribution name. Generates a Python method called
|         sample_X where X is the name given here (samples one
|         random number).
|     - pdfcall: Name of the method representing pdf (for more information,
|         see the __init__ method of this class). Optional; if not given
|         the name is pdf_X where X is the name given in the name parameter.
|
| maybeAppend(self, pdfevals, newtiles, xmn, xmx, ymn, ymx)
|
| sample(self, rg, n=1)
|     Generates random numbers that (approximately) follow the
|         distribution modeled by this class.
|     - n: The number of random numbers to generate.
|     Returns a list of 'n' random numbers.
|
| -----
| Data descriptors defined here:
|
| __dict__
|     dictionary for instance variables (if defined)
|
| __weakref__
|     list of weak references to the object (if defined)
|
| class FastLoadedDiceRoller(builtins.object)
|     Implements the Fast Loaded Dice Roller, which chooses a random number in [0, n)
|     where the probability that each number is chosen is weighted. The 'weights' is the

```

list of weights each 0 or greater; the higher the weight, the greater the probability. This sampler supports only integer weights.

Reference: Saad, F.A., Freer C.E., et al. "The Fast Loaded Dice Roller: A Near-Optimal Exact Sampler for Discrete Probability Distributions", in *AISTATS 2020: Proceedings of the 23rd International Conference on Artificial Intelligence and Statistics, Proceedings of Machine Learning Research* 108, Palermo, Sicily, Italy, 2020.

Methods defined here:

```
__init__(self, weights)
    Initialize self. See help(type(self)) for accurate signature.
```

```
codegen(self, name='sample_discrete')
    Generates standalone Python code that samples
    from the distribution modeled by this class.
    Idea from Leydold, et al.,
    "An Automatic Code Generator for
    Nonuniform Random Variate Generation", 2001.
    - name: Method name. Default: 'sample_discrete'.
```

```
next(self, randgen)
```

-----  
Data descriptors defined here:

```
__dict__
    dictionary for instance variables (if defined)

__weakref__
    list of weak references to the object (if defined)
```

```
class KVectorSampler(builtins.object)
    A K-Vector-like sampler of a continuous distribution
    with a known cumulative distribution function (CDF).
    Uses algorithms
    described in Arnas, D., Leake, C., Mortari, D., "Random
    Sampling using k-vector", Computing in Science &
    Engineering 21(1) pp. 94-107, 2019, and Mortari, D.,
    Neta, B., "k-Vector Range Searching Techniques".

    Methods defined here:

    __init__(self, cdf, xmin, xmax, pdf=None, nd=200)
        Initializes the K-Vector-like sampler.
        Parameters:
        - cdf: Cumulative distribution function (CDF) of the
          distribution. The CDF must be
          monotonically nondecreasing everywhere in the
          interval [xmin, xmax] and must output values in [0, 1];
          for best results, the CDF should
          be increasing everywhere in [xmin, xmax].
        - xmin: Maximum x-value to generate.
        - xmax: Maximum x-value to generate. For best results,
          the range given by xmin and xmax should cover all or
          almost all of the distribution.
        - pdf: Optional. Distribution's probability density
          function (PDF), to improve accuracy in the root-finding
          process.
        - nd: Optional. Size of tables used in the sampler.
          Default is 200.
```

```

quantile(self, uniforms)
    Returns a list of 'n' numbers that correspond
    to the given uniform random numbers and follow
    the distribution represented by this sampler. 'uniforms'
    is a list of uniform random values in the interval
    [0, 1]. For best results, this sampler's range
    (xmin and xmax in the constructor)
    should cover all or almost all of the desired distribution and
    the distribution's CDF should be monotonically
    increasing everywhere (every number in the distribution's
    range has nonzero probability of occurring), since
    among other things,
    this method maps each uniform value to the
    range of CDFs covered by this distribution (that is,
    [0, 1] is mapped to [minCDF, maxCDF]), and
    uniform values in "empty" regions (regions with
    constant CDF) are handled by replacing those
    values with the minimum CDF value covered.

sample(self, rg, n)
    Returns a list of 'n' random numbers of
    the distribution represented by this sampler.
    - rg: A random generator (RandGen) object.

-----
Data descriptors defined here:

__dict__
    dictionary for instance variables (if defined)

__weakref__
    list of weak references to the object (if defined)

class OptimalSampler(builtins.object)
    Implements a sampler which chooses a random number in [0, n)
    where the probability that each number is chosen is weighted. The 'weights' is the
    list of weights each 0 or greater; the higher the weight, the greater
    the probability. This sampler supports only integer weights, but the sampler is
    entropy-optimal as long as the sum of those weights is of the form 2^k or 2^k-2^m.

    Reference: Feras A. Saad, Cameron E. Freer, Martin C. Rinard, and Vikash K.
Mansinghka.
    Optimal Approximate Sampling From Discrete Probability Distributions. Proc.
    ACM Program. Lang. 4, POPL, Article 36 (January 2020), 33 pages.

    Methods defined here:

    __init__(self, m)
        Initialize self. See help(type(self)) for accurate signature.

    codegen(self, name='sample_discrete')
        Generates standalone Python code that samples
        from the distribution modeled by this class.
        Idea from Leydold, et al.,
        "An Automatic Code Generator for
        Nonuniform Random Variate Generation", 2001.
        - name: Method name. Default: 'sample_discrete'.

    next(self, rg)

    nextFromMatrix(self, pm, rg)

```

```

-----
Data descriptors defined here:

__dict__
    dictionary for instance variables (if defined)

__weakref__
    list of weak references to the object (if defined)

class PascalTriangle(builtins.object)
    Generates the rows of Pascal's triangle, or the
    weight table for a binomial(n,1/2) distribution.

    Methods defined here:

    __init__(self)
        Initialize self. See help(type(self)) for accurate signature.

    aliasinfo(self, desiredRow)

    getrow(self, desiredRow)
        Calculates an arbitrary row of Pascal's triangle.

    next(self)
        Generates the next row of Pascal's triangle, starting with
        row 0. The return value is a list of row-number-choose-k
        values.

    nextto(self, desiredRow)
        Generates the row of Pascal's triangle with the given row number,
        skipping all rows in between. The return value is a list of
        row-number-choose-k values.

    row(self)
        Gets the row number of the row that will be generated
        the next time _next_ is called.

-----
Data descriptors defined here:

__dict__
    dictionary for instance variables (if defined)

__weakref__
    list of weak references to the object (if defined)

class RandomGen(builtins.object)
    A class that implements many methods for
    random number generation and sampling. It takes
    an underlying RNG as specified in the constructor.

    Methods defined here:

    __init__(self, rng=None)
        Initializes a new RandomGen instance.
        NOTES:

        1. Assumes that 'rng' implements
        a 'randint(a, b)' method that returns a random
        integer in the interval [a, b]. Currently, this
        class assumes 'a' is always 0.

```



2. 'rndint' (and functions that ultimately call it) may be slower than desirable if many random numbers are needed at once. Ways to improve the performance of generating many random numbers at once include vectorization (which is often PRNG specific) and multithreading (which is too complicated to show here).

`ball_point(self, dims, radius=1)`  
Generates an independent and uniform random point inside a 'dims'-dimensional ball (disc, solid sphere, etc.) centered at the origin.

`bernoulli(self, p)`  
Returns 1 at probability p, 0 otherwise.

`beta(self, a, b, nc=0)`  
Generates a beta-distributed random number.  
'a' and 'b' are the two parameters of the beta distribution, and 'nc' is a parameter such that 'nc' other than 0 indicates a `_noncentral_` distribution.

`binomial(self, trials, p, n=None)`

`binomial_int(self, trials, px, py)`

`cauchy(self)`

`choice(self, list)`

`derangement(self, list)`  
Returns a copy of list with each of its elements moved to a different position.

`derangement_algorithm_s(self, list)`  
Returns a copy of 'list' with each of its elements moved to a different position (a derangement), but with the expected number of cycle lengths in probability, even though the list need not be a uniformly randomly chosen derangement. Uses importance sampling.  
Reference:  
J.R.G. Mendonça, "Efficient generation of random derangements with the expected distribution of cycle lengths", arXiv:1809.04571v4 [stat.CO], 2020.

`derangement_algorithm_t(self, list)`  
Returns a copy of 'list' with each of its elements moved to a different position (a derangement), but with the expected number of cycle lengths in probability, even though the list need not be a uniformly randomly chosen derangement. Reference:  
J.R.G. Mendonça, "Efficient generation of random derangements with the expected distribution of cycle lengths", arXiv:1809.04571v4 [stat.CO], 2020.

`diceRoll(self, dice, sides=6, bonus=0)`

`dirichlet(alphas)`

`discretegen(self, probs)`

Generates a random integer in  $[0, n)$ , where the probability of drawing each integer is specified as a list of probabilities that sum to 1, where  $n$  is the number of probabilities. This method is optimal, or at least nearly so, in terms of the number of random bits required to generate the number on average. This method implements a solution to exercise 3.4.2 of chapter 15 of Luc Devroye's `_Non-Uniform Random Variate Generation_`, 1986.

- `probs`. List of probability objects, where for each item in the probability list, the integer 'i' is chosen with probability `'probs[i]'`. Each probability object provides access to a binary expansion of the probability, which must be a real number in the interval  $[0, 1]$ . The binary expansion is a sequence of zeros and ones expressed as follows: The first binary digit is the half digit, the second is the quarter digit, the third is the one-eighth digit, and so on. Note that any probability with a terminating binary expansion (except 0) can be implemented by "subtracting" 1 from the expansion and then appending an infinite sequence of ones at the end. The probability object must implement the following three methods:
  - `reset()`: Resets the probability object to the first digit in the binary expansion.
  - `nextbit()`: Gets the next digit in the binary expansion.
  - `eof()`: Gets whether the end of the binary expansion was reached (True or False), meaning the rest of the digits in the expansion are all zeros.

The probability object will have to be mutable for this method to work.

The `BinaryExpansion` class is a convenient way to express numbers as probability objects that meet these criteria. Each probability object can also be a float, int, or `Fraction` in the interval  $[0, 1]$ .

`expoNumerator(self, denom)`

Generates the numerator of an exponential random number with a given denominator, using von Neumann's algorithm ("Various techniques used in connection with random digits", 1951).

`expoRatio(self, base, rx=1, ry=1)`

Generates an exponential random number (in the form of a ratio, or two-element list) given the rate `'rx'/'ry'` and the base `'base'`. The number will have the denominator `'base*rx'`.

`exponential(self, lamda=1.0)`

`exprandfill(self, a, bits)`

Fills the unsampled bits of the given exponential random number 'a' as necessary to make a number whose fractional part has 'bits' many bits. If the number's fractional part already has that many bits or more, the number is rounded using the round-to-nearest, ties to even rounding rule. Returns the resulting number as a multiple of  $2^{\text{'bits'}}$ .

`exprandless(self, a, b)`

Determines whether one partially-sampled exponential number is less than another; returns True if so and False otherwise. During

```

    the comparison, additional bits will be sampled in both numbers
    if necessary for the comparison.

expandnew(self, lamdanum=1, lamdaden=1)
    Returns an object to serve as a partially-sampled
    exponential random number with the given
    rate 'lamdanum'/'lamdaden'. The object is a list of five numbers:
    the first is a multiple of 1/(2^X), the second is X, the third is the integer
    part (initially -1 to indicate the integer part wasn't sampled yet),
    and the fourth and fifth are the lamda parameter's
    numerator and denominator, respectively. Default for 'lamdanum'
    and 'lamdaden' is 1.
    The number created by this method will be "empty"
    (no bits sampled yet).

frechet(self, a, b, mu=0)

gamma(self, mean, b=1.0, c=1.0, d=0.0)
    Generates a random number following a gamma distribution.

gaussian_copula(self, cov)

geoellipsoid_point(self, a=6378.137, invf=298.2572236)
    Generates an independent and uniform random
    point on the surface of a geoellipsoid. The
    geoellipsoid uses the following parameters:
    a - semimajor axis (distance from the center of
    the geoellipsoid to the equator). The default
    is the WGS 84 ellipsoid's semimajor axis
    in kilometers.
    invf - inverse flattening. The default is the
    WGS 84 ellipsoid's inverse flattening.

geometric(self, p)

gumbel(self, a, b)

hypercube_point(self, dims, sizeFromCenter=1)
    Generates an independent and uniform random point on the surface of a 'dims'-
dimensional
    hypercube (square, cube, etc.)
    centered at the origin.

hypergeometric(self, trials, ones, count)

hypersphere_point(self, dims, radius=1)
    Generates an independent and uniform random point on the surface of a 'dims'-
dimensional
    hypersphere (circle, sphere, etc.)
    centered at the origin.

integersWithSum(self, n, total)
    Returns a list of 'n' integers 0 or greater that sum to 'total'.
    The combination is chosen uniformly at random among all
    possible combinations.

integers_from_pdf(self, pdf, mn, mx, n=1)
    Generates one or more random integers from a discrete probability
    distribution expressed as a probability density
    function (PDF), which is also called the probability mass
    function for discrete distributions. The random integers
    will be in the interval [mn, mx]. `n` random integers will be

```

generated. ``pdf`` is the PDF; it takes one parameter and returns, for that parameter, a weight indicating the relative likelihood that a random integer will equal that parameter.  
The area under the "curve" of the PDF need not be 1.  
By default, ``n`` is 1.

`integers_from_u01(self, u01, pmf)`

Transforms one or more random numbers into numbers (called quantiles) that follow a discrete distribution, assuming the distribution produces only integers 0 or greater.  
- ``u01`` is a list of uniform random numbers, in  $[0, 1]$ .  
- ``pmf`` is the probability mass function (PMF) of the discrete distribution; it takes one parameter and returns, for that parameter, the probability that a random number is equal to that parameter (each probability is in the interval  $[0, 1]$ ).  
The area under the PMF must be 1; it is not enough for the PMF to be correct up to a constant.

`intsInRangeSortedWithSum(self, numSamples, numPerSample, mn, mx, sum)`

Generates one or more combinations of `'numPerSample'` numbers each, where each combination's numbers sum to `'sum'` and are listed in sorted order, and each number is in the interval `'[mn, mx]'`.  
The combinations are chosen uniformly at random.  
`'mn'`, `'mx'`, and `'sum'` may not be negative. Returns an empty list if `'numSamples'` is zero.  
The algorithm is thanks to a [\\_Stack Overflow\\_](#) answer (`'questions/61393463'`) by John McClane.  
Raises an error if there is no solution for the given parameters.

`intsInRangeWithSum(self, numSamples, numPerSample, mn, mx, sum)`

Generates one or more combinations of `'numPerSample'` numbers each, where each combination's numbers sum to `'sum'` and are listed in any order, and each number is in the interval `'[mn, mx]'`.  
The combinations are chosen uniformly at random.  
`'mn'`, `'mx'`, and `'sum'` may not be negative. Returns an empty list if `'numSamples'` is zero.  
The algorithm is thanks to a [\\_Stack Overflow\\_](#) answer (`'questions/61393463'`) by John McClane.  
Raises an error if there is no solution for the given parameters.

`intsInRangesWithSum(self, numSamples, ranges, total)`

Generates one or more combinations of `'len(ranges)'` numbers each, where each combination's numbers sum to `'total'`, and each number has its own valid range. `'ranges'` is a list of valid ranges for each number; the first item in each range is the minimum value and the second is the maximum value. For example, `'ranges'` can be `[[1,4],[3,5],[2,6]]`, which says that the first number must be in the interval  $[1, 4]$ , the second in  $[3, 5]$ , and the third in  $[2, 6]$ .  
The combinations are chosen uniformly at random.  
Neither the integers in the `'ranges'` list nor `'total'` may be negative. Returns an empty

```

    list if 'numSamples' is zero.
    This is a modification I made to an algorithm that
    was contributed in a Stack Overflow
    answer (`questions/61393463`) by John McClane.
    Raises an error if there is no solution for the given
    parameters.

kth_smallest_of_n_u01(self, k, n)
    Generates the kth smallest number among n random numbers
    in the interval [0, 1].

kthsmallest(self, n, k, b)
    Generates the 'k'th smallest 'b'-bit uniform random
    number out of 'n' of them.

kthsmallest_urand(self, n, k)
    Generates the 'k'th smallest 'b'-bit uniform random
    number out of 'n' of them; returns the result in
    the form of a "u-rand", or a partially sampled uniform
    random number (Karney, "Sampling exactly from the normal distribution").

latlon(self)
    Generates an independent and uniform random latitude and
    longitude, in radians. West and south coordinates
    are negative.

lognormal(self, mu=0.0, sigma=0.0)

lower_bound_copula(self)

mcmc(self, pdf, n)
    Generates 'n' random numbers that follow
    the probability density given in 'pdf' using
    a Markov-chain Monte Carlo algorithm, currently
    Metropolis--Hastings. The resulting random numbers
    are not independent, but are often close to
    being independent. 'pdf' takes one number as
    a parameter and returns a number 0 or greater.
    The area under the curve (integral) of 'pdf'
    need not be equal to 1.

mcmc2(self, pdf, n)
    Generates 'n' pairs of random numbers that follow
    the probability density given in 'pdf' using
    a Markov-chain Monte Carlo algorithm, currently
    Metropolis--Hastings. The resulting random pairs
    are not independent, but are often close to
    being independent. 'pdf' takes one parameter,
    namely, a list of two numbers giving a sampled
    point and returns a number 0 or greater.
    The volume under the surface (integral) of 'pdf'
    need not be equal to 1.

monte_carlo_integrate(self, func, bounds, samples=1000)
    Estimates the integral (volume) of a function within the
    given bounds using Monte Carlo integration, which generates
    an estimate using the help of randomization.
    func - Function to integrate. Takes the same number
    of parameters as the length of bounds.
    bounds - Bounds of integration at each dimension.
    An N-length array of arrays. Each array in turn
    contains two items: the lower bound and upper bound

```

for that dimension.  
samples - Number of times to sample the bounds of  
integration randomly. The default is 1000 samples.  
Returns an array containing two items: the estimated  
integral and the standard error.

moyal(self, mu=0, sigma=1)

Sample from a Moyal distribution, using the  
method given in C. Walck, "Handbook on  
Statistical Distributions for Experimentalists",  
pp. 93-94.

multinomial(self, trials, weights)

multinormal(self, mu, cov)

multinormal\_n(self, mu, cov, n=1)

multipoisson(self, firstmean, othermeans)

Multivariate Poisson distribution (as found in Mathematica).

multivariate\_t(self, mu, cov, df)

Multivariate t-distribution, mu is the mean (can be None),  
cov is the covariance matrix, and df is the degrees of freedom.

negativeMultinomial(self, succ, failures)

Negative multinomial distribution.

Models the number of failures of one or more  
kinds before a given number of successes happens.

succ: Number of successes.

failures: Contains probabilities for each kind of failure.

The sum of probabilities must be less than 1.

Returns: A list containing a random number  
of failures of each kind of failure.

negativebinomial(self, successes, p)

negativebinomialint(self, successes, px, py)

Generates a negative binomial random number, defined  
here as the number of failures before 'successes' many  
successful trials, where the probability of success in  
each trial is px/py.

nonzeroIntegersWithSum(self, n, total)

Returns a list of 'n' integers greater than 0 that sum to 'total'.  
The combination is chosen uniformly at random among all  
possible combinations.

normal(self, mu=0.0, sigma=1.0)

Generates a normally-distributed random number.

numbersWithSum(self, count, sum=1.0)

numbers\_from\_cdf(self, cdf, mn, mx, n=1)

Generates one or more random numbers from a continuous probability  
distribution by numerically inverting its cumulative  
distribution function (CDF).

- cdf: The CDF; it takes one parameter and returns,  
for that parameter, the probability that a random number will  
be less than or equal to that parameter.

- mn, mx: Sampling domain. The random number will be in the interval [mn, mx].
- n: How many random numbers to generate. Default is 1.

numbers\_from\_dist(self, pdf, mn=0, mx=1, n=1, bitplaces=53)

- Generates 'n' random numbers that follow a continuous distribution in an interval [mn, mx]. The distribution's PDF (probability density function) must be bounded from above (have a finite value) and be continuous almost everywhere in the interval. Implements section 4 of Devroye and Gravel, "The expected bit complexity of the von Neumann rejection algorithm", arXiv:1511.02273v2 [cs.IT], 2016.
- 'n' is the number of random numbers to generate. Default is 1.
  - 'pdf' is a procedure that takes three arguments: xmin, xmax, bitplaces, and returns an array of two items: the greatest lower bound of f(x) anywhere in the interval [xmin, xmax] (where f(x) is the PDF), and the least upper bound of f(x) anywhere there. Both bounds are multiples of  $2^{-\text{bitplaces}}$ .
  - 'bitplaces' is an accuracy expressed as a number of bits after the binary point. The random number will be a multiple of  $2^{-\text{bitplaces}}$ , or have a smaller granularity. Default is 53.
  - 'mn' and 'mx' express the interval. Both are optional and are set to 0 and 1, respectively, by default.

numbers\_from\_dist\_inversion(self, icdf, n=1, digitplaces=53, base=2)

- Generates 'n' random numbers that follow a continuous or discrete probability distribution, using the inversion method. Implements section 5 of Devroye and Gravel, "Sampling with arbitrary precision", arXiv:1502.02539v5 [cs.IT], 2015.
- 'n' is the number of random numbers to generate. Default is 1.
  - 'icdf' is a procedure that takes three arguments: u, ubits, digitplaces, and returns a number within  $\text{base}^{\text{digitplaces}}$  of the True inverse CDF (inverse cumulative distribution function, or quantile function) of  $u/\text{base}^{\text{ubits}}$ , and is monotonic for a given value of 'digitplaces'.
  - 'digitplaces' is an accuracy expressed as a number of digits after the point. Each random number will be a multiple of  $\text{base}^{\text{digitplaces}}$ , or have a smaller granularity. Default is 53.
  - base is the digit base in which the accuracy is expressed. Default is 2 (binary). (Note that 10 means decimal.)

numbers\_from\_pdf(self, pdf, mn, mx, n=1, steps=100)

- Generates one or more random numbers from a continuous probability distribution expressed as a probability density function (PDF). The random number will be in the interval [mn, mx]. 'n' random numbers will be generated. 'pdf' is the PDF; it takes one parameter and returns, for that parameter, a weight indicating the relative likelihood that a random number will be close to that parameter. 'steps' is the number of subintervals between sample points of the PDF. The area under the curve of the PDF need not be 1. By default, 'n' is 1 and 'steps' is 100.

numbers\_from\_u01(self, u01, pdf, cdf, mn, mx, ures=None)

- Transforms one or more random numbers into numbers (called quantiles) that follow a continuous probability distribution, based on (probability density function) and/or its CDF (cumulative distribution function).
- u01: List of uniform random numbers in [0, 1] that will be transformed into numbers that follow the distribution.
  - pdf: The PDF; it takes one parameter and returns, for that parameter, the relative probability that a

its PDF

random number close to that number is chosen. The area under the PDF need not be 1 (this method works even if the PDF is only known up to a normalizing constant). Optional if a CDF is given.

- cdf: The CDF; it takes one parameter and returns, for that parameter, the probability that a random number will be less than or equal to that parameter. Optional if a PDF is given. For best results, the CDF should be monotonically nondecreasing everywhere in the interval [xmin, xmax] and must output values in [0, 1]; for best results, the CDF should be increasing everywhere in [xmin, xmax].
- mn, mx: Sampling domain. The random number will be in the interval [mn, mx]. For best results, the range given by mn and mx should cover all or almost all of the distribution.
- ures - Maximum approximation error tolerable, or "u-resolution". Default is  $10^{-8}$ . Currently used only if a PDF is given.

pareto(self, minimum, alpha)

partialshuffle(self, list, k)  
Does a partial shuffle of a list's items (stops when 'k' items are shuffled); the shuffled items will appear at the end of the list. Returns 'list'.

piecewise\_linear(self, values, weights)

piecewise\_linear\_n(self, values, weights, n=1)

poisson(self, mean)  
Generates a random number following a Poisson distribution.

poissonint(self, mx, my)  
Generates a random number following a Poisson distribution with mean mx/my.

polya\_int(self, sx, sy, px, py)  
Generates a negative binomial (Polya) random number, defined here as the number of failures before 'successes' many successful trials (sx/sy), where the probability of success in each trial is px/py.

powerlognormal(self, p, sigma=1.0)  
Power lognormal distribution, as described in NIST/SEMATECH e-Handbook of Statistical Methods, [<http://www.itl.nist.gov/div898/handbook/>,] (<http://www.itl.nist.gov/div898/handbook/>,) accessed Jun. 9, 2018, sec. 1.3.6.6.14.

powernormal(self, p)  
Power normal distribution, as described in NIST/SEMATECH e-Handbook of Statistical Methods, [<http://www.itl.nist.gov/div898/handbook/>,] (<http://www.itl.nist.gov/div898/handbook/>,) accessed Jun. 9, 2018, sec. 1.3.6.6.13.

product\_copula(self, n=2)

quantile\_urands(self, icdf, urands, digitplaces=53)  
Finds the quantile of 'n' uniform random numbers expressed as "u-rands", or partially-sampled uniform random numbers (Karney, "Sampling exactly from the normal distribution"). Implements section 5 of Devroye and Gravel, "Sampling with arbitrary



precision", arXiv:1502.02539v5 [cs.IT], 2015.

| - 'urands' is a list of "u-rands", or partially-sampled uniform random numbers.  
Each u-rand is a list of two items, namely a multiple of  $1/2^X$ , followed by X. For example,  
the following generates a list of five empty

| u-rands: ``[[0,0] for i in range(5)]``.

- | - 'icdf' is a procedure that takes three arguments: u, ubits, digitplaces,  
and returns a number within  $2^{\text{digitplaces}}$  of the True inverse  
CDF (inverse cumulative distribution function, or quantile function)  
of  $u/2^{\text{ubits}}$ , and is monotonic for a given value of 'digitplaces'.
- | - 'digitplaces' is an accuracy expressed as a number of bits after the  
point. Each quantile will be a multiple of  $2^{\text{digitplaces}}$ ,  
or have a smaller granularity. Default is 53.

| Example: The following example generates the maximum of 10  
random numbers, to an accuracy of  $2^{53}$ .

| `ur=randgen.kthsmallest_urand(10, 10)`  
| `maxrand=randgen.quantile_urands(icdf, [ur], 53)[0]`

| `randbit(self)`

| `randbits(self, n)`  
| Generates an n-bit random integer.

| `randomwalk_posneg1(self, n)`  
| Random walk of uniform positive and negative steps.

| `randomwalk_u01(self, n)`  
| Random walk of uniform 0-1 random numbers.

| `rayleigh(self, a)`  
| Generates a random number following a Rayleigh distribution.

| `rndint(self, maxInclusive)`

| `rndint_fastdiceroller(self, maxInclusive)`

| `rndintexc(self, maxExclusive)`

| `rndintexcrange(self, minInclusive, maxExclusive)`

| `rndinrange(self, minInclusive, maxInclusive)`

| `rndrange(self, minInclusive, maxInclusive)`

| `rndrangemaxexc(self, minInclusive, maxExclusive)`

| `rndrangeminexc(self, mn, mx)`

| `rndrangeminmaxexc(self, mn, mx)`

| `rndu01(self)`

| `rndu01oneexc(self)`

| `rndu01zeroexc(self)`

| `rndu01zerooneexc(self)`

| `sample(self, list, k)`

| `sattolo(self, list)`

```

        Puts the elements of 'list' in random order, choosing
        from among all cyclic permutations (Sattolo's algorithm).
        Returns 'list'.

    shell_point(self, dims, outerRadius=1, innerRadius=0.5)
        Generates an independent and uniform random point inside a 'dims'-dimensional
        spherical shell (donut, hollow sphere, etc.)
        centered at the origin.

    shuffle(self, list)
        Puts the elements of 'list' in random order (does an
        in-place shuffle). Returns 'list'.

    simplex_point(self, points)
        Generates an independent and uniform random point on the surface of an N-
dimensional
        simplex (line segment, triangle, tetrahedron, etc.)
        with the given coordinates.

    slicesample(self, pdf, n, xstart=0.1)
        Slice sampling of R. M. Neal.
        Generates 'n' random numbers that follow
        the probability density given in 'pdf' using
        slice sampling. The resulting random numbers
        are not independent, but are often close to
        being independent. 'pdf' takes one number as
        a parameter and returns a number 0 or greater.
        The area under the curve (integral) of 'pdf'
        need not be equal to 1. 'xstart' should be
        chosen such that `pdf(xstart)>0`.

    spsa_minimize(self, func, guess, iterations=200, constrain=None, a=None, c=None,
acap=None)
        Tries to find a choice of parameters that minimizes the value
        of a scoring function, also called the objective function or loss
        function, starting from an initial guess. This method uses an
        algorithm called "simultaneous perturbation
        stochastic approximation", which is a randomized
        search for the minimum value of the objective function.
        func - Objective function, a function that calculates a score for the
        given array of parameters and returns that score. The score is a
        single number; the lower the score, the better.
        The score can be negative. (Note that the problem of maximizing
        the score is the same as minimizing it except
        that the score's sign is reversed at the end.)
        guess - Initial guess for the best choice of parameters. This is an
        array of parameters, each of which is a number. This array has
        as many items as the array passed to 'func'.
        iterations - Maximum number of iterations in which to run the
        optimization process. Default is 200.
        constrain - Optional. A function that takes the given array of
        parameters and constrains them to fit the bounds of a valid
        array of parameters. This function modifies the array in place.
        a - Optional. A setting used in the optimization process; greater than 0.
        c - Optional. A setting used in the optimization process; greater than 0. As a
guideline,
        'c' is about equal to the "standard deviation of the measurement noise"
        for several measurements at the initial guess, and is a "small positive
        number" if measurements are noise-free (Spall 1998). Default
        is 0.001.
        acap - Optional. A setting used in the optimization process; an
        integer greater than 0.

```

```

stable(self, alpha, beta)
    Generates a random number following a stable distribution.

stable0(self, alpha, beta, mu=0, sigma=1)
    Generates a random number following a 'type 0' stable distribution.

surface_point(self, f, bounds, ngrad, gmax)
    Generates a uniform random point on
    a parametric surface, using a rejection
    approach developed by Williamson, J.F.,
    "Random selection of points distributed on
    curved surfaces", Physics in Medicine & Biology 32(10), 1987.
- f: Takes two parameters (u and v) and returns
    a 3-element array expressing
    a 3-dimensional position at the given point.
- bounds: Two 2-element arrays expressing bounds
    for u and v. Of the form [[umin, umax], [vmin,
    vmax]].
- ngrad: Takes two parameters (u and v) and returns
    the norm of the gradient (stretch factor)
    at the given point. Can be None, in which
    the norm-of-gradient is calculated numerically.
- gmax: Maximum norm-of-gradient
    for entire surface.

t_copula(self, cov, df)
    Multivariate t-copula. 'cov' is the covariance matrix
    and 'df' is the degrees of freedom.

triangular(self, startpt, midpt, endpt)

truncnormal(randgen, a, b)
    Samples from a truncated normal distribution in [a, b]; this method is
    designed to sample from either tail of that distribution.

    Reference:
    Botev, Z. and L'Ecuyer, P., 2019. Simulation from the Tail of the
    Univariate and Multivariate Normal Distribution. In Systems
    Modeling: Methodologies and Tools (pp. 115-132). Springer, Cham.

upper_bound_copula(self, n=2)

vonmises(self, mean, kappa)

weibull(self, a, b)
    Generates a Weibull-distributed random number.

weighted_choice(self, weights)

weighted_choice_n(self, weights, n=1)

wiener(self, st, en, step=1.0, mu=0.0, sigma=1.0)
    Generates random numbers following a Wiener
    process (Brownian motion). Each element of the return
    value contains a timestamp and a random number in that order.

zero_or_one(self, px, py)
    Returns 1 at probability px/py, 0 otherwise.

zero_or_one_exp_minus(self, x, y)
    Generates 1 with probability exp(-px/py); 0 otherwise.

```

```

Reference:
  Canonne, C., Kamath, G., Steinke, T., "The Discrete Gaussian
  for Differential Privacy", arXiv:2004.00010v2 [cs.DS], 2020.

zero_or_one_power(self, px, py, n)
  Generates 1 with probability (px/py)^n (where n can be positive, negative, or
zero); 0 otherwise.

zero_or_one_power_ratio(self, px, py, nx, ny)
  Generates 1 with probability (px/py)^(nx/ny) (where nx/ny can be positive,
negative, or zero); 0 otherwise.

-----
Data descriptors defined here:

__dict__
  dictionary for instance variables (if defined)

__weakref__
  list of weak references to the object (if defined)

-----
Data and other attributes defined here:

FPPRECISION = 53

FPRADIX = 2

MINEXPONENT = -1074

class RatioOfUniformsTiling(builtins.object)
  Produces a tiling for the purposes
  of fast sampling from a probability distribution via the
  ratio of uniforms method.

  - pdf: The probability density function (PDF); it takes one parameter and returns,
    for that parameter, the relative probability that a
    random number close to that number is chosen. The area under
    the PDF need not be 1; this method works even if the PDF
    is only known up to a normalizing constant, and even if
    the distribution has infinitely extending tails to the left and/or right.
    However, for the ratio of uniforms method to work, both pdf(x) and
    x*pdf(x) must be bounded from above (thus, if the distribution has
    tails, they must drop off at a faster than quadratic rate).
  - mode: X-coordinate of the PDF's highest peak or one of them,
    or a location close to it. Optional; default is 0.
  - y0, y1: Bounding coordinates for the ratio-of-uniforms tiling.
    For this class to work,  $y_0 \leq \min(x \sqrt{\text{pdf}(x)})$  and
 $y_1 \geq \max(x \sqrt{\text{pdf}(x)})$  for all x. Optional; the default is y0=-10, y1=10.
  - cycles - Number of recursion cycles in which to split tiles
    for the ratio-of-uniforms tiling. Default is 8.

  Additional improvements not yet implemented:
  Generalized ratio-of-uniforms in Hörmann et al., "Automatic
  Nonuniform Random Variate Generation", 2004.

  References:
  Section IV.7 of Devroye, L., "Non-Uniform Random Variate Generation", 1986.
  Section 4.5 of Fulger, D., "From phenomenological modelling of anomalous
  diffusion through continuous-time random walks and fractional
  calculus to correlation analysis of complex systems", dissertation,
  Philipps-Universität Marburg, 2009.

```

Methods defined here:

```
__init__(self, pdf, mode=0, y0=-10, y1=10, cycles=8)
    Initialize self. See help(type(self)) for accurate signature.

codegen(self, name, pdfcall=None)
    Generates Python code that samples
        (approximately) from the distribution estimated
        in this class. Idea from Leydold, et al.,
        "An Automatic Code Generator for
        Nonuniform Random Variate Generation", 2001.
    - name: Distribution name. Generates a Python method called
        sample_X where X is the name given here (samples one
        random number).
    - pdfcall: Name of the method representing pdf (for more information,
        see the __init__ method of this class). Optional; if not given
        the name is pdf_X where X is the name given in the name parameter.

maybeAppend(self, newtiles, xmn, xmx, ymn, ymx, depth=0)

sample(self, rg, n=1)
    Generates random numbers that (approximately) follow the
        distribution modeled by this class.
    - n: The number of random numbers to generate.
    Returns a list of 'n' random numbers.

svg(self)
```

-----  
Data descriptors defined here:

```
__dict__
    dictionary for instance variables (if defined)

__weakref__
    list of weak references to the object (if defined)
```

```
class SortedAliasMethod(builtins.object)
    Implements a weighted sampling table
    where each weight must be in sorted
    order (ascending or descending).
    When many entries are in the table,
    the initialization is faster than with
    FastLoadedDiceRoller or VoseAlias. Reference:
    K. Bringmann and K. Panagiotou, "Efficient Sampling
    Methods for Discrete Distributions." In: Proc. 39th
    International Colloquium on Automata, Languages,
    and Programming (ICALP'12), 2012.
    - p: List of weights, in sorted order (ascending or
        descending).
```

Methods defined here:

```
__init__(self, p)
    Initialize self. See help(type(self)) for accurate signature.

next(self, rg)
```

-----  
Data descriptors defined here:

```

|   __dict__
|       dictionary for instance variables (if defined)
|
|   __weakref__
|       list of weak references to the object (if defined)
|
class VoseAlias(builtins.object)
|   Implements Vose's version of the alias sampler, which chooses a random number in [0,
n) |   where the probability that each number is chosen is weighted. The 'weights' is the
|   list of weights each 0 or greater; the higher the weight, the greater
|   the probability. This sampler supports integer or non-integer weights.
|
|   Reference:
|   Vose, Michael D. "A linear algorithm for generating random numbers with a given
|   distribution." IEEE Transactions on software engineering 17, no. 9 (1991): 972-975.
|
|   Methods defined here:
|
|   __init__(self, weights)
|       Initialize self. See help(type(self)) for accurate signature.
|
|   next(self, randgen)
|
|   -----
|   Data descriptors defined here:
|
|   __dict__
|       dictionary for instance variables (if defined)
|
|   __weakref__
|       list of weak references to the object (if defined)

```

## FUNCTIONS

numericalTable(func, x, y, n=100)

urandfill(rg, a, bits=53)

Fills the unsampled bits of the given u-rand 'a' as necessary to make a number with 'bits' many bits. If the u-rand already has that many bits or more, the u-rand is rounded using the round-to-nearest, ties to even rounding rule. Returns the resulting number as a multiple of  $2^{\text{'bits'}}$ . Default for 'bits' is 53.

- rg: An object that must supply a 'randbit' method that generates an unbiased random bit.

urandgreater(rg, a, b)

Determines whether the first u-rand is greater than another u-rand; returns True if so and False otherwise. During the comparison, additional bits will be sampled in both u-rands if necessary for the comparison.

- rg: An object that must supply a 'randbit' method that generates an unbiased random bit.
- a, b: The first and second u-rands.

urandless(rg, a, b)

Determines whether the first u-rand is less than another u-rand; returns True if so and False otherwise. During the comparison, additional bits will be sampled in both u-rands if necessary for the comparison.

- rg: An object that must supply a 'randbit' method that generates an unbiased random bit.
- a, b: The first and second u-rands.

urandnew()  
Returns an object to serve as a partially-sampled uniform random number called a "u-rand" (Karney, "Sampling exactly from the normal distribution").  
A u-rand is a list of two numbers: the first is a multiple of  $1/(2^X)$ , and the second is X.

The urand created by this method will be "empty" (no bits sampled yet).

FILE  
/home/rooster/Documents/SharpDevelopProjects/peteroupc.github.io/randomgen.py

Help on module fixed:

NAME  
fixed

CLASSES  
builtins.object  
Fixed

```
class Fixed(builtins.object)
| Fixed-point numbers, represented using integers that store multiples
| of 2-BITS. They are not necessarily faster than floating-point numbers, nor
| do they necessarily have the same precision or resolution of floating-point
| numbers. The main benefit of fixed-point numbers is that they improve
| determinism for applications that rely on non-integer real numbers (notably
| simulations and machine learning applications), in the sense that the operations
| given here deliver the same answer for the same input across computers,
| whereas floating-point numbers have a host of problems that make repeatable
| results difficult, including differences in their implementation, rounding
| behavior, and order of operations, as well as nonassociativity of
| floating-point numbers.
|
| The operations given here are not guaranteed to be "constant-time"
| (non-data-dependent and branchless) for all relevant inputs.
|
| Any copyright to this file is released to the Public Domain. In case this is not
| possible, this file is also licensed under Creative Commons Zero version 1.0.
|
| Methods defined here:
|
| __abs__(self)
|
| __add__(a, b)
|
| __cmp__(self, other)
|
| __div__(a, b)
|
| __eq__(self, other)
|     Return self==value.
|
| __float__(a)
|
| __floordiv__(a, b)
|
| __ge__(self, other)
|     Return self>=value.
|
| __gt__(self, other)
|     Return self>value.
```

```

__init__(self, i)
    Initialize self. See help(type(self)) for accurate signature.

__int__(a)

__le__(self, other)
    Return self<=value.

__lt__(self, other)
    Return self<value.

__mod__(a, b)

__mul__(a, b)

__ne__(self, other)
    Return self!=value.

__neg__(self)

__pos__(self)

__rdiv__(a, b)

__repr__(self)
    Return repr(self).

__rtruediv__(a, b)

__str__(self)
    Return str(self).

__sub__(a, b)

__truediv__(a, b)

acos(a)
    Calculates an approximation of the inverse cosine of the given number.

asin(a)
    Calculates an approximation of the inverse sine of the given number.

atan2(y, x)
    Calculates the approximate measure, in radians, of the angle formed by the
    X axis and a line determined by the origin and the given coordinates of a 2D
    point. This is also known as the inverse tangent.

cos(a)
    Calculates the approximate cosine of the given angle; the angle is in radians.
    For the fraction size used by this class, this method is accurate to within
    1 unit in the last place of the correctly rounded result for all inputs
    in the range  $[-\pi*2, \pi*2]$ .
    This method's accuracy decreases beyond that range.

exp(a)
    Calculates an approximation of e (base of natural logarithms) raised
    to the power of this number. May raise an error if this number
    is extremely high.

floor(a)

log(a)

```



Calculates an approximation of the natural logarithm of this number.

`pow(a, b)`

Calculates an approximation of this number raised to the power of another number.

`round(a)`

`sin(a)`

Calculates the approximate sine of the given angle; the angle is in radians.  
For the fraction size used by this class, this method is accurate to within  
1 unit in the last place of the correctly rounded result for all inputs  
in the range  $[-\pi^2, \pi^2]$ .  
This method's accuracy decreases beyond that range.

`sqrt(a)`

Calculates an approximation of the square root of the given number.

`tan(a)`

Calculates the approximate tangent of the given angle; the angle is in radians.  
For the fraction size used by this class, this method is accurate to within  
2 units in the last place of the correctly rounded result for all inputs  
in the range  $[-\pi^2, \pi^2]$ .  
This method's accuracy decreases beyond that range.

-----  
Static methods defined here:

`v(i)`

Converts a string, integer, Decimal, or other number type into  
a fixed-point number. If the parameter is a Fixed, returns itself.  
If the given number is a non-integer, returns the closest value to  
a Fixed after rounding using the round-to-nearest-ties-to-even  
rounding mode. The parameter is recommended to be a string  
or integer, and is not recommended to be a ``float``.

-----  
Data descriptors defined here:

`__dict__`

dictionary for instance variables (if defined)

`__weakref__`

list of weak references to the object (if defined)

-----  
Data and other attributes defined here:

`ArcTanBitDiff = 9`

`ArcTanFrac = 29`

`ArcTanHTable = [0, 294906490, 137123709, 67461703, 33598225, 16782680, ...]`

`ArcTanTable = [421657428, 248918914, 131521918, 66762579, 33510843, 16...`

`BITS = 20`

`ExpK = 648270061`

`HALF = 524288`

`HalfPiArcTanBits = 843314856`

```

HalfPiBits = 1647099
HalfPiHighRes = 130496653328243011213339889301986179
HighResFrac = 116
Ln2ArcTanBits = 372130559
Log2Bits = 726817
LogMin = 157286.4
MASK = 1048575
PiAndHalfHighRes = 391489959984729033640019667905958538
PiArcTanBits = 1686629713
PiBits = 3294199
PiHighRes = 260993306656486022426679778603972359
QuarterPiArcTanBits = 421657428
SinCosK = 326016435
TwoTimesPiArcTanBits = 3373259426
TwoTimesPiBits = 6588397
TwoTimesPiHighRes = 521986613312972044853359557207944718
__hash__ = None

```

#### FILE

```
/home/rooster/Documents/SharpDevelopProjects/peteroupc.github.io/fixed.py
```

Help on module bernoulli:

#### NAME

```
bernoulli
```

#### CLASSES

```
builtins.object
Bernoulli
```

```

class Bernoulli(builtins.object)
|   This class contains methods that generate Bernoulli random numbers,
|   (either 1 or heads with a given probability, or 0 or tails otherwise).
|   This class also includes implementations of so-called "Bernoulli factories",
algorithms
|   that turn coins biased one way into coins biased another way.
|   Written by Peter O.
|
|   References:
|   - Flajolet, P., Pelletier, M., Soria, M., "On Buffon machines and numbers",
|   arXiv:0906.5560v2 [math.PR], 2010.
|   - Huber, M., "Designing perfect simulation algorithms using local correctness",
|   arXiv:1907.06748v1 [cs.DS], 2019.
|   - Huber, M., "Nearly optimal Bernoulli factories for linear functions",
|   arXiv:1308.1562v2 [math.PR], 2014.

```

- Huber, M., "Optimal linear Bernoulli factories for small mean problems", arXiv:1507.00843v2 [math.PR], 2016.
- Łatuszyński, K., Kosmidis, I., Papaspiliopoulos, O., Roberts, G.O., "Simulating events of unknown probabilities via reverse time martingales", arXiv:0907.4018v2 [stat.CO], 2009/2011.
- Goyal, V. and Sigman, K. 2012. On simulating a class of Bernstein polynomials. ACM Transactions on Modeling and Computer Simulation 22(2), Article 12 (March 2012), 5 pages.
- Morina, G., Łatuszyński, K., et al., "From the Bernoulli Factory to a Dice Enterprise via Perfect Sampling of Markov Chains", arXiv:1912.09229v1 [math.PR], 2019.
- Shaddin Dughmi, Jason D. Hartline, Robert Kleinberg, and Rad Niazadeh. 2017. Bernoulli Factories and Black-Box Reductions in Mechanism Design. In *Proceedings of 49th Annual ACM SIGACT Symposium on the Theory of Computing*, Montreal, Canada, June 2017 (STOC'17).
- Gonçalves, F. B., Łatuszyński, K. G., Roberts, G. O. (2017). Exact Monte Carlo likelihood-based inference for jump-diffusion processes.
- Vats, D., Gonçalves, F. B., Łatuszyński, K. G., Roberts, G. O. Efficient Bernoulli factory MCMC for intractable likelihoods, arXiv:2004.07471v1 [stat.CO], 2020.
- Mendo, Luis. "An asymptotically optimal Bernoulli factory for certain functions that can be expressed as power series." *Stochastic Processes and their Applications* 129, no. 11 (2019): 4366-4384.
- Canonne, C., Kamath, G., Steinke, T., "The Discrete Gaussian for Differential Privacy", arXiv:2004.00010v2 [cs.DS], 2020.
- Lee, A., Doucet, A. and Łatuszyński, K., 2014. Perfect simulation using atomic regeneration with application to Sequential Monte Carlo, arXiv:1407.5770v1 [stat.CO]

Methods defined here:

```

__init__(self)
    Creates a new instance of the Bernoulli class.

add(self, f1, f2, eps=Fraction(1, 20))
    Addition Bernoulli factory:  $B(p), B(q) \Rightarrow B(p+q)$  (Dughmi et al. 2017)
    - f1, f2: Functions that return 1 if heads and 0 if tails.
    - eps: A Fraction in (0, 1). eps must be chosen so that  $p+q \leq 1 - \text{eps}$ ,
      where p and q are the probability of heads for f1 and f2, respectively.

alt_series(self, f, series)
    Alternating-series Bernoulli factory:  $B(p) \rightarrow B(s[0] - s[1]*p + s[2]*p^2 - \dots)$ 
    (Łatuszyński et al. 2011).
    - f: Function that returns 1 if heads and 0 if tails.
    - series: Object that generates each coefficient of the series starting with the
first.
        Each coefficient must be less than or equal to the previous and all of them
must
        be 1 or less.
    Implements the following two methods: reset() resets the object to the first
        coefficient; and next() generates the next coefficient.

arctan_n_div_n(self, f)
    Arctan div N:  $B(p) \rightarrow B(\arctan(p)/p)$ . Uses a uniformly-fast special case of
    the two-coin Bernoulli factory, rather than the even-parity construction in
    Flajolet's paper, which is not uniformly fast.
    Reference: Flajolet et al. 2010.
    - f: Function that returns 1 if heads and 0 if tails.

bernoulli_x(self, f, x)
    Bernoulli factory with a given probability:  $B(p) \Rightarrow B(x)$  (Mendo 2019).
    Mendo calls Bernoulli factories "non-randomized" if their randomness

```

is based entirely on the underlying coin.  
 - f: Function that returns 1 if heads and 0 if tails.  
 - x: Desired probability, in  $[0, 1]$ .

```
bernstein(self, f, alpha)
    Bernstein polynomial Bernoulli factory:  $B(p) \Rightarrow B(\text{Bernstein}(\alpha))$ 
    (Goyal and Sigman 2012).
    - f: Function that returns 1 if heads and 0 if tails.
    - alpha: List of Bernstein coefficients for the Bernstein polynomial,
      whose degree is this list's length minus 1.
      For this to work, each coefficient must be in  $[0, 1]$ .

coin(self, c)
    Convenience method to generate a function that returns
    1 (heads) with the given probability c (which must be in  $[0, 1]$ )
    and 0 (tails) otherwise.

complement(self, f)
    Complement (NOT):  $B(p) \Rightarrow B(1-p)$  (Flajolet et al. 2010)
    - f: Function that returns 1 if heads and 0 if tails.

conditional(self, f1, f2, f3)
    Conditional:  $B(p), B(q), B(r) \Rightarrow B((1-r)*q+r*p)$  (Flajolet et al. 2010)
    - f1, f2, f3: Functions that return 1 if heads and 0 if tails.

cos(self, f)
    Cosine Bernoulli factory:  $B(p) \Rightarrow B(\cos(p))$ . Special
    case of Algorithm3 of reverse-time martingale paper.

disjunction(self, f1, f2)
    Disjunction (OR):  $B(p), B(q) \Rightarrow B(p+q-p*q)$  (Flajolet et al. 2010)
    - f1, f2: Functions that return 1 if heads and 0 if tails.

divoneplus(self, f)
    Divided by one plus p:  $B(p) \Rightarrow B(1/(1+p))$ , implemented
    as a special case of the two-coin construction. Prefer over even-parity
    for being uniformly fast.
    - f: Function that returns 1 if heads and 0 if tails.
    Note that this function is slow as the probability of heads approaches 1.

eps_div(self, f, eps)
    Bernoulli factory as follows:  $B(p) \rightarrow B(\text{eps}/p)$  (Lee et al. 2014).
    - f: Function that returns 1 if heads and 0 if tails.
    - eps: Fraction in  $(0, 1)$ , must be chosen so that  $\text{eps} < p$ , where p is
      the probability of heads.

evenparity(self, f)
    Even parity:  $B(p) \Rightarrow B(1/(1+p))$  (Flajolet et al. 2010)
    - f: Function that returns 1 if heads and 0 if tails.
    Note that this function is slow as the probability of heads approaches 1.

exp_minus(self, f)
    Exp-minus Bernoulli factory:  $B(p) \rightarrow B(\exp(-p))$  (Łatuszyński et al. 2011).
    - f: Function that returns 1 if heads and 0 if tails.

exp_minus_ext(self, f, c=0)
    Extension to the exp-minus Bernoulli factory of (Łatuszyński et al. 2011):
     $B(p) \rightarrow B(\exp(-p - c))$ 
    To the best of my knowledge, I am not aware
    of any article or paper that presents this particular
    Bernoulli factory (before my articles presenting
    accurate beta and exponential generators).
```

```

- f: Function that returns 1 if heads and 0 if tails.
- c: Integer part of exp-minus. Default is 0.

fill_geometric_bag(self, bag, precision=53)

geometric_bag(self, u)
    Bernoulli factory for a uniformly-distributed random number in (0, 1)
    (Flajolet et al. 2010).
- u: List that holds the binary expansion, from left to right, of the uniformly-
    distributed random number. Each element of the list is 0, 1, or None (meaning
    the digit is not yet known). The list may be expanded as necessary to put
    a new digit in the appropriate place in the binary expansion.

linear(self, f, cx, cy=1, eps=Fraction(1, 20))
    Linear Bernoulli factory:  $B(p) \Rightarrow B((cx/cy)*p)$  (Huber 2016).
- f: Function that returns 1 if heads and 0 if tails.
- cx, cy: numerator and denominator of c; the probability of heads (p) is
multiplied
    by c. c must be 0 or greater. If  $c > 1$ , c must be chosen so that  $c*p \leq 1 -$ 
eps.
    - eps: A Fraction in (0, 1). If  $c > 1$ , eps must be chosen so that  $c*p \leq 1 -$  eps.

linear_lowprob(self, f, cx, cy=1, m=Fraction(249, 500))
    Linear Bernoulli factory which is faster if the probability of heads is known
    to be less than half:  $B(p) \Rightarrow B((cx/cy)*p)$  (Huber 2016).
- f: Function that returns 1 if heads and 0 if tails.
- cx, cy: numerator and denominator of c; the probability of heads (p) is
multiplied
    by c. c must be 0 or greater. If  $c > 1$ , c must be chosen so that  $c*p \leq m <$ 
1/2.
    - m: A Fraction in (0, 1/2). If  $c > 1$ , m must be chosen so that  $c*p \leq m < 1/2$ .

linear_power(self, f, cx, cy=1, i=1, eps=Fraction(1, 20))
    Linear-and-power Bernoulli factory:  $B(p) \Rightarrow B((p*cx/cy)^i)$  (Huber 2019).
- f: Function that returns 1 if heads and 0 if tails.
- cx, cy: numerator and denominator of c; the probability of heads (p) is
multiplied
    by c. c must be 0 or greater. If  $c > 1$ , c must be chosen so that  $c*p \leq 1 -$ 
eps.
    - i: The exponent. Must be an integer and 0 or greater.
    - eps: A Fraction in (0, 1). If  $c > 1$ , eps must be chosen so that  $c*p \leq 1 -$  eps.

logistic(self, f, cx=1, cy=1)
    Logistic Bernoulli factory:  $B(p) \rightarrow B(cx*p/(cy+cx*p))$  or
     $B(p) \rightarrow B((cx/cy)*p/(1+(cx/cy)*p))$  (Morina et al. 2019)
- f: Function that returns 1 if heads and 0 if tails. Note that this function
can
    be slow as the probability of heads approaches 0.
- cx, cy: numerator and denominator of c; the probability of heads (p) is
multiplied
    by c. c must be in (0, 1).

mean(self, f1, f2)
    Mean:  $B(p), B(q) \Rightarrow B((p+q)/2)$  (Flajolet et al. 2010)
- f1, f2: Functions that return 1 if heads and 0 if tails.

old_linear(self, f, cx, cy=1, eps=Fraction(1, 20))
    Linear Bernoulli factory:  $B(p) \Rightarrow B((cx/cy)*p)$ . Older algorithm given in (Huber
2014).
- f: Function that returns 1 if heads and 0 if tails.
- cx, cy: numerator and denominator of c; the probability of heads (p) is
multiplied

```

```

        by c. c must be 0 or greater. If c > 1, c must be chosen so that  $c \cdot p < 1 - \text{eps}$ .
        - eps: A Fraction in (0, 1). If c > 1, eps must be chosen so that  $c \cdot p < 1 - \text{eps}$ .

one_div_pi(self)
    Generates 1 with probability 1/pi.
    Reference: Flajolet et al. 2010.

power(self, f, ax, ay=1)
    Power Bernoulli factory:  $B(p) \Rightarrow B(p^{ax/ay})$ . (case of (0, 1) provided by
    Mendo 2019).
    - f: Function that returns 1 if heads and 0 if tails.
    - ax, ay: numerator and denominator of the desired power to raise the probability
    of heads to. This power must be 0 or greater.

powerseries(self, f)
    Power series Bernoulli factory:  $B(p) \Rightarrow B(1 - c(0) \cdot (1-p) + c(1) \cdot (1-p)^2 +$ 
     $c(2) \cdot (1-p)^3 + \dots)$ , where  $c(i) = \text{c}[i] / \text{sum}(c)$  (Mendo 2019).
    - f: Function that returns 1 if heads and 0 if tails.
    - c: List of coefficients in the power series, all of which must be
    non-negative integers.

probgenfunc(self, f, rng)
    Probability generating function Bernoulli factory:  $B(p) \Rightarrow B(E[p^x])$ , where x is
rng()
    (Dughmi et al. 2017).  $E[p^x]$  is the expected value of  $p^x$  and is also known
    as the probability generating function.
    - f: Function that returns 1 if heads and 0 if tails.
    - rng: Function that returns a non-negative integer at random.
    Example (Dughmi et al. 2017): if 'rng' is Poisson(lamda) we have
    an "exponentiation" Bernoulli factory as follows:
     $B(p) \Rightarrow B(\exp(p \cdot \text{lamda} - \text{lamda}))$ 

product(self, f1, f2)
    Product (conjunction; AND):  $B(p), B(q) \Rightarrow B(p \cdot q)$  (Flajolet et al. 2010)
    - f1, f2: Functions that return 1 if heads and 0 if tails.

randbit(self)
    Generates a random bit that is 1 or 0 with equal probability.

rndintexc(self, maxexc)
    Returns a random integer in [0, maxexc).

sin(self, f)
    Sine Bernoulli factory:  $B(p) \Rightarrow B(\sin(p))$ . Special
    case of Algorithm3 of reverse-time martingale paper.

square(self, f1, f2)
    Square:  $B(p) \Rightarrow B(1-p)$ . (Flajolet et al. 2010)
    - f1, f2: Functions that return 1 if heads and 0 if tails.

twocoin(self, f1, f2, c1=1, c2=1, beta=1)
    Two-coin Bernoulli factory:  $B(p), B(q) \Rightarrow$ 
     $B(c1 \cdot p \cdot \text{beta} / (\text{beta} \cdot (c1 \cdot p + c2 \cdot q) - (\text{beta} - 1) \cdot (c1 + c2)))$ 
    (Gonçalves et al. 2017, Vats et al. 2020; in Vats et al.,
    C1,p1 corresponds to cy and C2,p2 corresponds to cx).
    Logistic Bernoulli factory is a special case with q=1, c2=1, beta=1.
    - f1, f2: Functions that return 1 if heads and 0 if tails.
    - c1, c2: Factors to multiply the probabilities of heads for f1 and f2,
respectively.
    - beta: Early rejection parameter ("portkey" two-coin factory).
    When beta = 1, the formula simplifies to  $B(c1 \cdot p / (c1 \cdot p + c2 \cdot q))$ .

```

```

twofacpower(self, fbase, fexponent)
    Bernoulli factory B(p, q) => B(p^q).
    Based on algorithm from (Mendo 2019),
    but changed to accept a Bernoulli factory
    rather than a fixed value for the exponent.
    To the best of my knowledge, I am not aware
    of any article or paper that presents this particular
    Bernoulli factory (before my articles presenting
    accurate beta and exponential generators).
    - fbase, fexponent: Functions that return 1 if heads and 0 if tails.
      The first is the base, the second is the exponent.

zero_or_one(self, px, py)
    Returns 1 at probability px/py, 0 otherwise.

zero_or_one_arctan_n_div_n(self, x, y=1)
    Generates 1 with probability arctan(x/y)*y/x; 0 otherwise.
    x/y must be in [0, 1]. Uses a uniformly-fast special case of
    the two-coin Bernoulli factory, rather than the even-parity construction in
    Flajolet's paper, which is not uniformly fast.
    Reference: Flajolet et al. 2010.

zero_or_one_exp_minus(self, x, y)
    Generates 1 with probability exp(-x/y); 0 otherwise.
    Reference: Canonne et al. 2020.

zero_or_one_loglp(self, x, y=1)
    Generates 1 with probability log(1+x/y); 0 otherwise.
    Reference: Flajolet et al. 2010. Uses a uniformly-fast special case of
    the two-coin Bernoulli factory, rather than the even-parity construction in
    Flajolet's paper, which is not uniformly fast.

zero_or_one_pi_div_4(self)
    Generates 1 with probability pi/4.
    Reference: Flajolet et al. 2010.

zero_or_one_power(self, px, py, n)
    Generates 1 with probability (px/py)^n (where n can be
    positive, negative, or zero); 0 otherwise.

zero_or_one_power_ratio(self, px, py, nx, ny)
    Generates 1 with probability (px/py)^(nx/ny) (where nx/ny can be
    positive, negative, or zero); 0 otherwise.

-----
Data descriptors defined here:

__dict__
    dictionary for instance variables (if defined)

__weakref__
    list of weak references to the object (if defined)

```

FILE  
/home/rooster/Documents/SharpDevelopProjects/peteroupc.github.io/bernoulli.py

Help on module interval:

NAME  
interval

DESCRIPTION

```
# Implements interval numbers and interval arithmetic, backed
# by Decimal values.
#
# Written by Peter O. Any copyright to this file is released to the Public Domain.
# In case this is not possible, this file is also licensed under Creative Commons Zero
# (https://creativecommons.org/publicdomain/zero/1.0/).
#
```

## CLASSES

```
builtins.object
Interval
```

```
class Interval(builtins.object)
| An interval of two Decimal values.
|
| Methods defined here:
|
| __add__(self, v)
|
| __max__(a, b)
|
| __min__(a, b)
|
| __mul__(self, v)
|
| __neg__(self)
|
| __pow__(self, v)
|
| __radd__(self, v)
|
| __repr__(self)
|     Return repr(self).
|
| __rmul__(self, v)
|
| __rsub__(self, v)
|
| __rtruediv__(self, v)
|
| __sub__(self, v)
|
| __truediv__(self, v)
|
| abs(self)
|
| ceil(self)
|
| clamp(self, a, b)
|
| clampleft(self, a)
|
| cos(self)
|
| exp(self)
|
| floor(self)
|
| isAccurateTo(self, v)
|
| log(self)
```



```

| magnitude(self)
|
| mignitude(self)
|
| pi(prec=56)
|
| pow(self, v)
|
| rem(self, v)
|
| sin(self)
|
| sqrt(self)
|
| tan(self)
|
| width(self)
|     NOTE: Not rigorous!
|
|-----
| Static methods defined here:
|
| __new__(cl, v, sup=None, prec=None)
|     Create and return a new object.  See help(type) for accurate signature.
|
|-----
| Data descriptors defined here:
|
| __dict__
|     dictionary for instance variables (if defined)
|
| __weakref__
|     list of weak references to the object (if defined)

```

#### FILE

/home/rooster/Documents/SharpDevelopProjects/peteroupc.github.io/interval.py

Help on module moore:

#### NAME

moore

#### DESCRIPTION

```

# Implements the Moore Rejection Sampler.
#
# Written by Peter O. Any copyright to this file is released to the Public Domain.
# In case this is not possible, this file is also licensed under Creative Commons Zero
# (https://creativecommons.org/publicdomain/zero/1.0/).
#

```

#### CLASSES

```

builtins.object
MooreSampler

```

```

class MooreSampler(builtins.object)
| Moore rejection sampler, for generating independent samples
| from continuous distributions in a way that minimizes error,
| if the distribution's PDF (probability density function)
| uses "well-defined" arithmetic expressions.
| It can sample from one-dimensional or multidimensional
| distributions. It can also sample from so-called "transdimensional
| distributions" if the distribution is the union of several component

```

distributions that may have different dimensions and are associated with one of several `_labels_`.

Parameters:

- `pdf`: A function that specifies the PDF. It takes a single parameter that differs as follows, depending on the case:
  - One-dimensional case: A single Interval. (An Interval is a mathematical object that specifies upper and lower bounds of a number.)
  - Multidimensional case: A list of Intervals, one for each dimension.
  - Transdimensional case (`numLabels > 1`): A list of two items: the Interval or Intervals, followed by a label number (an integer in `[0, numLabels)`). This function returns an Interval. For best results, the function should use interval arithmetic throughout. The area under the PDF need not equal 1 (this sampler works even if the PDF is only known up to a normalizing constant).
- `mn, mx`: Specifies the sampling domain of the PDF. There are three cases:
  - One-dimensional case: Both `mn` and `mx` are numbers giving the domain, which in this case is `[mn, mx]`.
  - Multidimensional case: Both `mn` and `mx` are lists giving the minimum and maximum bounds for each dimension in the sampling domain. In this case, both lists must have the same size.
  - Transdimensional case: Currently, this class assumes the component distributions share the same sampling domain, which is given depending on the preceding two cases.For this sampler to work, the PDF must be "locally Lipschitz" in the sampling domain, meaning that the function is continuous everywhere in the domain, and has no slope that tends to a vertical slope anywhere in that domain.
- `numLabels`: The number of labels associated with the distribution, if it's a transdimensional distribution. Optional; the default is 1.
- `bitAccuracy`: Bit accuracy of the sampler; the sampler will sample from a distribution (truncated to the sampling domain) that is close to the ideal distribution by  $2^{\text{bitAccuracy}}$ . The default is 53.

Reference:

Sainudiin, Raazesh, and Thomas L. York. "An Auto-Validating, Trans-Dimensional, Universal Rejection Sampler for Locally Lipschitz Arithmetical Expressions." *Reliable Computing* 18 (2013): 15-54.

The following reference describes an optimization, not yet implemented here: Sainudiin, R., 2014. An Auto-validating Rejection Sampler for Differentiable Arithmetical Expressions: Posterior Sampling of Phylogenetic Quartets. In *Constraint Programming and Decision Making* (pp. 143-152). Springer, Cham.

Methods defined here:

```
__init__(self, pdf, mn, mx, numLabels=1, bitAccuracy=53)
    Initialize self. See help(type(self)) for accurate signature.

acceptRate(self)

sample(self)
    Samples a number or vector (depending on the number of dimensions)
    from the distribution and returns that sample.
    If the sampler is transdimensional (the number of labels is greater than 1),
    instead returns a list containing the sample and a random label in the
    interval [0, numLabels), in that order.
```

-----  
Data descriptors defined here:

```
|  __dict__  
|      dictionary for instance variables (if defined)  
|  
|  __weakref__  
|      list of weak references to the object (if defined)
```

FILE

/home/rooster/Documents/SharpDevelopProjects/peteroupc.github.io/moore.py