# SampleSpace

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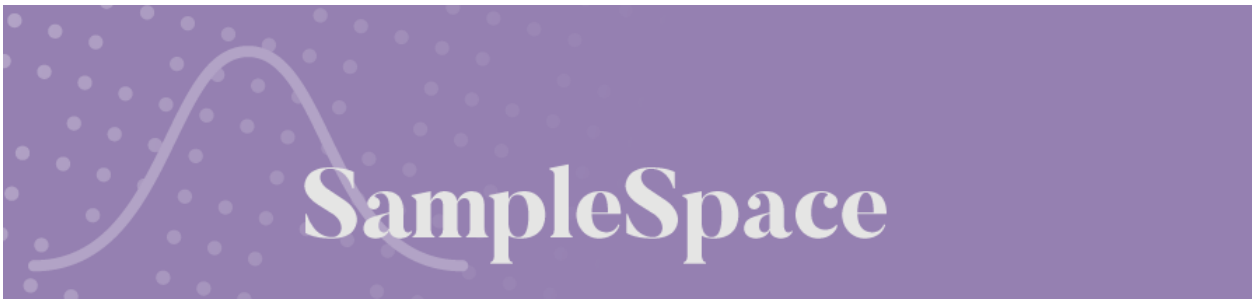
# SUBMODULES




SampleSpace is a cross-platform library for describing and sampling from random distributions.

While SampleSpace is primarily intended for creating procedurally-generated content, it is also useful for Monte-Carlo simulations, unit testing, and anywhere that flexible, repeatable random numbers are required.

Installation is simple:

```
$ pip install pysamplespace
```

SampleSpace's only dependency is xxHash, though it optionally offers additional functionality if PyYAML is installed.

SampleSpace was created by Coriander V. Pines and is available under the BSD 3-Clause License.

The source is available on GitLab.

CHAPTER

ONE

# SAMPLESPACE.REPEATABLERANDOM - REPEATABLE RANDOM SEQUENCES

*RepeatableRandomSequence* allows for generating repeatable, deterministic random sequences. It is compatible `random` as a drop-in replacement.

A key feature of *RepeatableRandomSequence* is its ability to get, serialize, and restore internal state. This is especially useful when generating procedural content from a fixed seed.

A *RepeatableRandomSequence* can also be used for unit testing by replacing the built-in `random` module. Because each random sequence is deterministic and repeatable for a given seed, expected values can be recorded and compared against within unit tests.

*RepeatableRandomSequence* produces high-quality pseudo-random values. See *Random Generator Quality* for results from randomness tests.

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**class** samplespace.repeatablerandom.**RepeatableRandomSequence**(*seed=None*)

A deterministic and repeatable random number generator compatible with Python's builtin `random` module.

**Parameters** **seed** (*int*, *str*, *bytes*, *bytearray*) – The sequence's initial seed. See the *seed()* method below for more details.

RepeatableRandomSequence.**BLOCK_SIZE_BITS: int = 64**

The number of bits generated for each unique index.

RepeatableRandomSequence.**BLOCK_MASK: int = 18446744073709551615**

A bitmask corresponding to `(1 << BLOCK_SIZE_BITS) - 1`

## 1.1 Bookkeeping functions

RepeatableRandomSequence.**seed**(*value=None*) → None

Re-initialize the random generator with a new seed. Resets the sequence to its first value.

> **Caution:** This method cannot be called from within *cascade()*, and will raise a `RuntimeError` if attempted.

**Parameters** **value** (*int*, *str*, *bytes*, *bytearray*) – The value to seed with. If this is a sequence type, the sequence is first hashed with seed 0.

**Raises** **ValueError** – If the seed value is not a supported type.

RepeatableRandomSequence.**getseed**()
Returns: the original value passed to *RepeatableRandomSequence()* or *seed()*.

RepeatableRandomSequence.**getstate**() → *samplespace.repeatablerandom.RepeatableRandomSequenceState*
Returns an opaque object representing the sequence's current state, used for saving, restoring, and serializing the sequence. This object can be passed to *setstate()* to restore the sequence's state.

RepeatableRandomSequence.**setstate**(*state:* samplespace.repeatablerandom.RepeatableRandomSequenceState) → None
Restore the sequence's state from previous call to *getstate()*.

RepeatableRandomSequence.**reset**() → None
Reset the sequence to the beginning, setting *index* to 0.

> **Caution:** This method cannot be called from within *cascade()*, and will raise a RuntimeError if attempted.

RepeatableRandomSequence.**index**
The sequence's current index. Generating random values will always increase the index.

> **Tip:** Prefer *getstate()* and *setstate()* over index manipulation when saving and restoring state.

> **Caution:** The index cannot be read or written within *cascade()*, and will raise a RuntimeError if attempted.

**Type** int

RepeatableRandomSequence.**getnextblock**() → int
Get a block of random bits from the random generator.

> **Tip:** Calling this method will advance the sequence exactly one time. The resulting index depends on whether or not the call occurs within a cascade.

**Returns** A block of *BLOCK_SIZE_BITS* random bits as an int

RepeatableRandomSequence.**getrandbits**(*k: int*) → int
Generate an int with *k* random bits.

This method may call *getnextblock()* multiple times if *k* is greater than *BLOCK_SIZE_BITS*; regardless of the number of calls, the index will only advance once.

> **Tip:** Note that `k == 0` is a valid input, which will advance the sequence even though no elements are chosen.

**Parameters** **k** (*int*) – The number of random bits to generate.

**Returns** A random integer in [0, `max(2^k, 1)`)

RepeatableRandomSequence.**cascade**()
Returns a context manager that defines a generation cascade.

Cascades are not required for most applications, but may be useful for certain advanced procedural generation techniques.

A cascade allows multiple random samples to be treated as part the same logical unit.

For example, generating a random position in space can be treated as a single "transaction" by grouping the fields into a single cascade:

```
>>> print(rrs.index)
10
>>> with rrs.cascade():
...     x = rrs.random()  # index is 10
...     y = rrs.random()  # index is the previously-generated random block
...     z = rrs.random()  # index is the previously generated random block
...
>>> print(rrs.index)
11
```

The use of cascades ensure that random values are repeatable and based only on the number of previously-generated values, not the type of the values themselves. This is often useful when creating procedurally-generated content using pre-defined seeds.

While cascading, subsequent calls to random generation functions use the result of the most recently generated random data rather than incrementing the index. When a cascade completes, the index is set to one more than the index when the cascade began.

**class** samplespace.repeatablerandom.**RepeatableRandomSequenceState**(*_seed: Any*, *_hash_input: bytes*, *_index: int*)

An object representing a *RepeatableRandomSequence*'s internal state.

**as_dict**()

Return the sequence state as a dictionary for serialization.

**classmethod from_dict**(*as_dict*)

Construct a new sequence state from a dictionary, as returned by *as_dict()*.

### Examples

```
>>> rrs = RepeatableRandomSequence()
>>>
>>> state_as_dict = rrs.getstate().as_dict()
>>> state_as_dict
{'seed': 0, 'hash_input': 'NMlqzcrbG7s=', 'index': 0}
>>>
>>> new_state = RepeatableRandomSequenceState.from_dict(state_as_dict)
>>> rrs.setstate(new_state)
```

## 1.2 Integer distributions

RepeatableRandomSequence.**randrange**(*start: int*, *stop: Optional[int] = None*, *step: int = 1*) → int
Generate a random integer from `range(start[, stop][, step])`.

If only one argument is provided, samples from `range(start)`.

**Parameters**

- **start** (*int*) – The starting point for the range, inclusive. If *stop* is `None`, this becomes the endpoint for the range, exclusive. None *None*
- **stop** (*int, optional*) – The end point for the range, exclusive.
- **step** (*int, default 1*) – Steps between possible values. May not be 0.

**Raises**

- **TypeError** – if any arguments are not integral.
- **ValueError** – if step is 0

RepeatableRandomSequence.**randint**(*a: int*, *b: int*) → int
Generate a random integer in the range [*a*, *b*].

This is an alias for `randrange(a, b + 1)`, included for compatibility with the builtin `random` module.

RepeatableRandomSequence.**randbytes**(*num_bytes*) → bytes
Generate a sequence of random bytes.

The index will only increment once, regardless of the number of bytes in the sequence.

This method produces similar results to

```
with rrs.cascade():
    result = bytes([rrs.randrange(256) for _ in range(num_bytes])
```

but offers significantly-improved performance and does not discard excess random bits.

**Returns** A `bytes` object with *num_bytes* random integers in [0, 255].

RepeatableRandomSequence.**geometric**(*mean: float*, *include_zero: bool = False*) → int
Generate integers according to a geometric distribution.

If *include_zero* is `False`, returns integers from 1 to infinity according to $\Pr(x = k) = p(1-p)^{k-1}$ where $p = \frac{1}{mean}$.

If *include_zero* is `True`, returns integers from 0 to infinity according to $\Pr(x = k) = p(1-p)^{k}$ where $p = \frac{1}{mean+1}$.

**Parameters**

- **mean** (*float*) – The desired mean value.
- **include_zero** (*bool*) – Whether or not the distribution's support includes zero.

**Raises** **ValueError** – if *mean* is less than 1 if *include_zero* is `False`, or less than 0 if *include_zero* is `True`.

RepeatableRandomSequence.**finitegeometric**(*s: float*, *n: int*)
Generate a random integer according to a geometric-like distribution with exponent *s* and finite support $\{1, \ldots, n\}$.

The finite geometric distribution is defined by the equation

$$\Pr(x = k) = \frac{s^k}{\sum_{i=1}^{N} s^i}$$

**Raises** **ValueError** – if n is not at least 1

RepeatableRandomSequence.**zipfmandelbrot**(*s: float*, *q: float*, *n: int*)

Generate a random integer according to a Zipf-Mandelbrot distribution with exponent $s$, offset $q$, and support $\{1, \ldots, n\}$.

The Zipf-Mandelbrot distribution is defined by the equation

$$\Pr(x = k) = \frac{(k + q)^{-s}}{\sum_{i=1}^{N} (i + q)^{-s}}$$

**Raises** **ValueError** – if n is not at least 1

## 1.3 Categorical distributions

RepeatableRandomSequence.**choice**(*sequence: Sequence*)

Choose a single random element from within a sequence.

**Raises** **IndexError** – if the sequence is empty.

RepeatableRandomSequence.**choices**(*population: Sequence*, *weights: Optional[Sequence[float]] = None*, ***, *cum_weights: Optional[Sequence[float]] = None*, *k: int = 1*) → Sequence

Choose *k* elements from a population, **with** replacement.

Either relative (via *weights*) or cumulative (via *cum_weights*) weights may be specified. If no weights are specified, selections are made uniformly with equal probability.

---

**Tip:** Note that `k == 0` is a valid input, which returns an empty list an advances the sequence once even though no elements are chosen.

---

**Parameters**

- **population** (*sequence*) – The population to sample from, which may include duplicate elements.
- **weights** (*sequence[float], optional*) – Relative weights for each element in the population. Need not sum to 1.
- **cum_weights** (*sequence[float], optional*) – Cumulative weights for each element in the population, as calculated by something like `list(accumulate(weights))`.
- **k** (*int*) – The number of elements to choose.

**Raises**

- **IndexError** – The population is empty.
- **ValueError** – The length of *weights* or *cum_weights* does not match the population size.
- **TypeError** – Both *weights* and *cum_weights* are specified.

RepeatableRandomSequence.**shuffle**(*sequence: Sequence*) → None
Shuffle a sequence in place.

The index is only incremented once.

RepeatableRandomSequence.**sample**(*population*, *k: int*) → Sequence
Choose *k* unique random elements from a population, **without** replacement.

Elements are returned in selection order, so all subsets of the returned list are valid samples.

If the population includes duplicate values, each occurrence is as distinct possible selection in the result.

---

**Tip:** Note that `k == 0` is a valid input, which returns an empty list an advances the sequence once even though no elements are chosen.

---

**Parameters**

- **population** (*list, tuple, set, range*) – The source population.
- **k** (*int*) – The number of samples to choose, no more than the total number of elements in population.

**Raises**

- **IndexError** – if population is empty.
- **ValueError** – if *k* is greater than the population size.

RepeatableRandomSequence.**chance**(*p: float*) → bool
Returns `True` with probability *p*, else `False`.

Alias for `random() < p`.

## 1.4 Continuous distributions

RepeatableRandomSequence.**random**() → float
Return a random float in [0.0, 1.0).

RepeatableRandomSequence.**uniform**(*a: float*, *b: float*) → float
Return a random float uniformly distributed in [*a*, *b*).

RepeatableRandomSequence.**triangular**(*low: float = 0.0*, *high: float = 1.0*, *mode: Optional[float] = None*) → float
Sample from a triangular distribution with lower limit *low*, upper limit *low*, and mode *mode*.

The triangular distribution is defined by

$$\mathrm{P}(x) = \begin{cases} 0 & \text{for } xl, \\ \frac{2(x-l)}{(h-l)(m-l)} & \text{for } l \le xh, \\ \frac{2}{h-l} & \text{for } x = m, \\ \frac{2(h-x)}{(h-l)(h-m)} & \text{for } mx \le h, \\ 0 & \text{for } hx \end{cases}$$

**Raises** **ValueError** – if the mode is not in [*low*, *high*].

RepeatableRandomSequence.**gauss**(*mu: float*, *sigma: float*) → float
Sample from a Gaussian distribution with parameters *mu* and *sigma*.

The Gaussian, or Normal distribution is defined by

$$\mathrm{P}(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

---

**Tip:** If multiple normally-distributed values are required, consider using `gausspair()` for improved performance.

---

RepeatableRandomSequence.**gausspair**(*mu: float*, *sigma: float*) → Tuple[float, float]
Return a pair of *independent* samples from a Gaussian distribution with parameters *mu* and *sigma*.

This method produces similar results to

```
with rrs.cascade():
    result = rrs.gauss(mu, sigma), rrs.gauss(mu, sigma)
```

but offers improved performance.

RepeatableRandomSequence.**lognormvariate**(*mu: float*, *sigma: float*) → float
Sample from a log-normal distribution with parameters *mu* and *sigma*.

The logarithms of values sampled from a log-normal distribution are normally distributed with mean *mu* and standard deviation *sigma*. The distribution is defined by

$$\mathrm{P}(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$$

RepeatableRandomSequence.**expovariate**(*lambd: float*) → float
Sample from an exponential distribution with rate *lambd*.

The probability density function for the exponential distribution is defined by $\mathrm{P}(x) = \lambda e^{-\lambda x}$ where $x \geq 0$

RepeatableRandomSequence.**vonmisesvariate**(*mu: float*, *kappa: float*) → float
Sample from a von Mises distribution with parameters *mu* and *kappa*.

Samples from a von Mises distribution represent randomly-chosen angles clustered around a mean angle. This distribution is an approximation to the wrapped normal distribution and is defined by

$$\mathrm{P}(x) = \frac{e^{\kappa \cos(x-\mu)}}{2\pi I_0(\kappa)}$$

where $I_0(\kappa)$ is the modified Bessel function of order 0.

**Parameters**

- **mu** (*float*) – The mean angle, in radians, around which to cluster.
- **kappa** (*float*) – The concentration parameter, which must be at least 0.

**Returns** An angle in radians within [0, *2 pi*)

RepeatableRandomSequence.**gammavariate**(*alpha: float*, *beta: float*) → float
Sample from a gamma distribution with parameters *alpha* and *beta*. Not to be confused with `math.gamma()`!

The gamma distribution is defined as

$$\mathrm{P}(x) = \frac{x^{\alpha-1} e^{-\frac{x}{\beta}}}{\Gamma(\alpha)\beta^{\alpha}}$$

> **Caution:** This implementation defines its parameters to match `random.gammavariate()`. The parametrization differs from most common definitions of the gamma distribution, as defined on Wikipedia, et al. Take care when setting *alpha* and *beta*!

**Raises** **ValueError** – if either *alpha* or *beta* is not greater than 0.

`RepeatableRandomSequence.`**`betavariate`**(*alpha: float*, *beta: float*) → float

Sample from a beta distribution with parameters *alpha* and *beta*.

The beta distribution is defined by

$$\mathrm{P}(x) = x^{\alpha-1}(1-x)^{\beta-1}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}$$

**Returns** A random, beta-distributed value in [0.0, 1.0]

**Raises** **ValueError** – if either alpha or beta is not greater than 0.

`RepeatableRandomSequence.`**`paretovariate`**(*alpha: float*) → float

Sample from a Pareto distribution with shape parameter *alpha* and minimum value 1.

The Pareto distribution has PDF

$$\mathrm{P}(x) = \frac{\alpha}{x^{\alpha+1}}$$

**Raises** **ValueError** – if *alpha* is zero.

`RepeatableRandomSequence.`**`weibullvariate`**(*alpha: float*, *beta: float*) → float

Sample from a Weibull distribution with scale parameter *alpha* and shape parameter *beta*.

The distribution is defined by

$$\mathrm{P}(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{k-1} e^{-(x/\alpha)^k}$$

where $x \geq 0$.

**Raises** **ValueError** – if *alpha* is zero.

`RepeatableRandomSequence.`**`normalvariate`**(*mu: float*, *sigma: float*) → float

Sample from a normal distribution with mean *mu* and standard variation *sigma*.

---

**Note:** Unlike `random.normalvariate()`, this is an alias for *gauss(mu, sigma)*. It is included for compatibility with the built-in `random` module.

---

## 1.5 Examples

Generating random values:

```
import samplespace

rrs = samplespace.RepeatableRandomSequence(seed=1234)

samples = [rrs.randrange(30) for _ in range(10)]
print(samples)
# Will always print:
# [21, 13, 28, 19, 16, 29, 28, 24, 29, 25]
```

Distinct seeds produce unique results:

```
import samplespace

# Each seed will generate a unique sequence of values
for seed in range(5):
    rrs = samplespace.RepeatableRandomSequence(seed=seed)
    samples = [rrs.random() for _ in range(5)]
    print('Seed: {0}\tResults: {1}'.format(
        seed,
        ' '.join('{:.3f}'.format(x) for x in samples)))
```

Results depend only on number of previous calls, not their type:

```
import samplespace

rrs = samplespace.RepeatableRandomSequence(seed=1234)

dummy = rrs.random()
x1 = rrs.random()

rrs.reset()
dummy = rrs.gauss(6.0, 2.0)
x2 = rrs.random()
assert x2 == x1

rrs.reset()
dummy = rrs.randrange(50)
x3 = rrs.random()
assert x3 == x1

rrs.reset()
dummy = list('abcdefg')
rrs.shuffle(dummy)
x4 = rrs.random()
assert x4 == x1

rrs.reset()
with rrs.cascade():
    dummy = [rrs.random() for _ in range(10)]
x5 = rrs.random()
assert x5 == x1
```

Replay random sequences using *RepeatableRandomSequence.reset()*:

```
import samplespace

rrs = samplespace.RepeatableRandomSequence(seed=1234)

samples = [rrs.random() for _ in range(10)]
print(' '.join(samples))

# Using reset() returns the sequence to its initial state
rrs.reset()
samples2 = [rrs.random() for _ in range(10)]
print(' '.join(samples2))
assert samples == sample2
```

Replay random sequences using *RepeatableRandomSequence.getstate()*/

*RepeatableRandomSequence.setstate()*:

```
import samplespace

rrs = samplespace.RepeatableRandomSequence(seed=12345)

# Generate some random values to advance the state
[rrs.random() for _ in range(100)]

# Save the state for later recall
state = rrs.getstate()
print(rrs.random())
# Will print 0.2736967629462168

# Generate some more values
[rrs.random() for _ in range(100)]

# Return the sequence to the saved state. The next value will match
# the value following when the state was saved.
rrs.setstate(state)
print(rrs.random())
# Will also print 0.2736967629462168
```

Replay random sequences using *RepeatableRandomSequence.index()*:

```
import samplespace

rrs = samplespace.RepeatableRandomSequence(seed=5)

# Generate a sequence of values
samples = [rrs.randrange(10) for _ in range(15)]
print(samples)
# Will print
# [0, 2, 2, 7, 9, 4, 1, 5, 5, 6, 7, 1, 7, 6, 8]

# Rewind the sequence by 5
rrs.index -= 5

# Generate a new sequence, will overlap by 5 elements
samples = [rrs.randrange(10) for _ in range(15)]
print(samples)
# Will print
# [7, 1, 7, 6, 8, 6, 6, 6, 3, 7, 6, 9, 5, 2, 7]
```

Serialize sequence state as simple data types:

```
import samplespace
import samplespace.repeatablerandom
import json

rrs = samplespace.RepeatableRandomSequence(seed=12345)

# Generate some random values to advance the state
[rrs.random() for _ in range(100)]

# Save the state for later recall
# State can be serialzied to a dict and serialized as JSON
state = rrs.getstate()
```

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```
state_as_dict = state.as_dict()
state_as_json = json.dumps(state_as_dict)
print(state_as_json)
# Prints {"seed": 12345, "hash_input": "gxzNfDj4Ypc=", "index": 100}

print(rrs.random())
# Will print 0.2736967629462168

# Generate some more values
[rrs.random() for _ in range(100)]

# Return the sequence to the saved state. The next value will match
# the value following when the state was saved.
new_state_as_dict = json.loads(state_as_json)
new_state = samplespace.repeatablerandom.RepeatableRandomSequenceState.from_dict(new_
↪state_as_dict)
rrs.setstate(new_state)
print(rrs.random())
# Will also print 0.2736967629462168
```

CHAPTER

TWO

# SAMPLESPACE.DISTRIBUTIONS - SERIALIZABLE PROBABILITY DISTRIBUTIONS

This module implements a number of useful probability distributions.

Each distribution can be sampled using any random number generator providing at least the same functionality as the `random` module; this includes *`samplespace.repeatablerandom.RepeatableRandomSequence`*.

The classes in this module are primarily intended for storing information on random distributions in configuration files using `Distribution.as_dict()`/*`distribution_from_dict()`* or `Distribution.as_list()`/*`distribution_from_list()`*. See the *Examples* section for examples on how to do this.

## 2.1 Integer distributions

**class** samplespace.distributions.**DiscreteUniform**(*min_val: int*, *max_val: int*)

Represents a discrete uniform distribution of integers in [*min_value*, *max_value*).

**as_dict**() → Dict

Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List

Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property max_val**

Read-only property for the distribution's upper limit.

**property min_val**

Read-only property for the distribution's lower limit.

**sample**(*rand*) → int

Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**Geometric**(*mean: float*, *include_zero: bool* = *False*)

Represents a geometric distribution.

If *include_zero* is `False`, returns integers from 1 to infinity according to $\Pr(x = k) = p(1-p)^{k-1}$ where $p = \frac{1}{mean}$.

If *include_zero* is `True`, returns integers from 0 to infinity according to $\Pr(x = k) = p(1-p)^k$ where $p = \frac{1}{mean+1}$.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property include_zero**
Read-only property for whether or not the distribution's support includes zero.

**property mean**
Read-only property for the distribution's mean.

**sample**(*rand*) → int
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**FiniteGeometric**(*s: float*, *n: int*)
Represents a geometric-like distribution with exponent *s* and finite support $\{1, \ldots, n\}$.

The finite geometric distribution is defined by the equation

$$\Pr(x = k) = \frac{s^k}{\sum_{i=1}^{N} s^i}$$

The distribution is defined such that each result is *s* times as likely to occur as the previous; i.e. $\Pr(x = k) = s\Pr(x = k - 1)$ over the support.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property n**
Read-only property for the number of values in the distribution's support.

**property s**
Read-only property for the distribution's *s* exponent.

**sample**(*rand*) → int
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**ZipfMandelbrot**(*s: float*, *q: float*, *n: int*)
Represents a Zipf-Mandelbrot distribution with exponent *s*, offset *q*, and support $\{1, \ldots, n\}$.

The Zipf-Mandelbrot distribution is defined by the equation

$$\Pr(x = k) = \frac{(k+q)^{-s}}{\sum_{i=1}^{N}(i+q)^{-s}}$$

When `q == 0`, the distribution becomes the Zipf distribution, and as *n* increases, it approaches the Zeta distribution.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property n**
Read-only property for the number of values in the distribution's support.

**property q**
Read-only property for the distribution's *q* offset.

**property s**
Read-only property for the distribution's *s* exponent.

**sample**(*rand*) → int
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**Bernoulli**(*p: float*)
Represents a Bernoulli distribution with parameter *p*.

Returns `True` with probability *p*, and `False` otherwise.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property p**
Read-only property for the distribution's *p* parameter.

**sample**(*rand*) → bool
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

## 2.2 Categorical distributions

**class** samplespace.distributions.**WeightedCategorical**(*items: Optional[Sequence[Tuple[float, Any]]] = None*, *population: Optional[Sequence] = None*, *weights: Optional[Sequence[float]] = None*, *, *cum_weights: Optional[Sequence[float]] = None*)

Represents a categorical distribution defined by a population and a list of relative weights.

Either *items*, *population* and *weights*, or *population* and *cum_weights* should be provided, not all three.

**Parameters**

- **items** (*Sequence[Tuple[Any]]*) – A sequence of tuples in the format (weight, relative value).
- **population** (*Sequence*) – A sequence of possible values.
- **weights** (*Sequence[float], optional*) – A sequence of relative weights corresponding to each item in the population. Must be the same length as the population list.
- **cum_weights** (*Sequence[float], optional*) – A sequence of cumulative weights corresponding to each item in the population. Must be the same length as the population list. Only one of *weights* and *cum_weights* should be provided.

**as_dict**() → Dict

Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List

Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property cum_weights**

A read-only property for the distribution's cumulative weights.

**property items**

A read-only property returning a sequence of tuples in the format (weight, relative value).

**property population**

A read-only property for the distribution's population.

**sample**(*rand*)

Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**UniformCategorical**(*population: Sequence*)

Represents a uniform categorical distribution over a given population.

**as_dict**() → Dict

Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List

Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property population**
A read-only property for the distribution's population.

**sample**(*rand*)
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**FiniteGeometricCategorical**(*population: Sequence*, *s: float*)
Represents a categorical distribution with weights corresponding to a finite geometric-like distribution with exponent *s*.

The finite geometric distribution is defined by the equation

$$\Pr(x = k) = \frac{s^k}{\sum_{i=1}^{N} s^i}$$

The distribution is defined such that each result is *s* times as likely to occur as the previous; i.e. $\Pr(x = k) = s\Pr(x = k - 1)$ over the support.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property cum_weights**
A read-only property for the distribution's cumulative weights.

**property items**
A read-only property returning a sequence of tuples in the format (weight, relative value).

**property n**
Read-only property for the number of values in the distribution's support.

**property population**
A read-only property for the distribution's population.

**property s**
Read-only property for the distribution's *s* exponent.

**sample**(*rand*)
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**ZipfMandelbrotCategorical**(*population: Sequence*, *s: float*, *q: float*)
Represents a categorical distribution with weights corresponding to a Zipf-Mandelbrot distribution with exponent *s* and offset *q*.

The Zipf-Mandelbrot distribution is defined by the equation

$$\Pr(x = k) = \frac{(k + q)^{-s}}{\sum_{i=1}^{N} (i + q)^{-s}}$$

When `q == 0`, the distribution becomes the Zipf distribution, and as *n* increases, it approaches the Zeta distribution.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property cum_weights**
A read-only property for the distribution's cumulative weights.

**property items**
A read-only property returning a sequence of tuples in the format (weight, relative value).

**property n**
Read-only property for the number of values in the distribution's support.

**property population**
A read-only property for the distribution's population.

**property q**
Read-only property for the distribution's *q* offset.

**property s**
Read-only property for the distribution's *s* exponent.

**sample**(*rand*)
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

## 2.3 Continuous distributions

**class** samplespace.distributions.**Constant**(*value*)
Represents a distribution that always returns a constant value.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**sample**(*rand*)
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**property value**
Read-only property for the distribution's constant value.

**class** samplespace.distributions.**Uniform**(*min_val: float = 0.0*, *max_val: float = 1.0*)
Represents a continuous uniform distribution with support [*min_val*, *max_val*).

The uniform distribution is defined as

$$\mathrm{P}(x) = \begin{cases} \frac{1}{b-a} & \text{for } x \in [a, b) \\ 0 & \text{otherwise} \end{cases}$$

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property max_val**
Read-only property for the distribution's upper limit.

**property min_val**
Read-only property for the distribution's lower limit.

**sample**(*rand*) → float
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**Gamma**(*alpha: float*, *beta: float*)
Represents a gamma distribution with parameters *alpha* and *beta*.

The gamma distribution is defined as

$$\mathrm{P}(x) = \frac{x^{\alpha-1} e^{-\frac{x}{\beta}}}{\Gamma(\alpha)\beta^{\alpha}}$$

**Caution:** This implementation defines its parameters to match `random.gammavariate()`. The parametrization differs from most common definitions of the gamma distribution, as defined on Wikipedia, et al. Take care when setting *alpha* and *beta*!

**property alpha**
Read-only property for the distribution's *alpha* parameter.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property beta**
Read-only property for the distribution's *beta* parameter.

**sample**(*rand*) → float
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**Triangular**(*low: float = 0.0*, *high: float = 1.0*, *mode: Optional[float] = None*)
Represents a triangular distribution with lower limit *low*, upper limit *low*, and mode *mode*.

The triangular distribution is defined by

$$\mathrm{P}(x) = \begin{cases} 0 & \text{for } xl, \\ \frac{2(x-l)}{(h-l)(m-l)} & \text{for } l \leq xh, \\ \frac{2}{h-l} & \text{for } x = m, \\ \frac{2(h-x)}{(h-l)(h-m)} & \text{for } mx \leq h, \\ 0 & \text{for } hx \end{cases}$$

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property high**
Read-only property for the distribution's upper bound.

**property low**
Read-only property for the distribution's lower bound.

**property mode**
Read-only property for the distribution's mode, if specified, otherwise `None`.

**sample**(*rand*) → float
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**LogNormal**(*mu: float = 0.0*, *sigma: float = 1.0*)
Represents a log-normal distribution with parameters *mu* and *sigma*.

The logarithms of values sampled from a log-normal distribution are normally distributed with mean *mu* and standard deviation *sigma*. The distribution is defined by

$$\mathrm{P}(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$$

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property mu**
Read-only property for the distribution's *mu* parameter.

**sample**(*rand*) → float
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**property sigma**
Read-only property for the distribution's *sigma* parameter.

**class** samplespace.distributions.**Exponential**(*lambd: float*)
Represents an exponential distribution with rate *lambd*.

The probability density function for the exponential distribution is defined by $\mathrm{P}(x) = \lambda e^{-\lambda x}$ where $x \geq 0$

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property lambd**
Read-only property for the distribution's rate parameter.

**sample**(*rand*) → float
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**VonMises**(*mu: float*, *kappa: float*)
Represents a von Mises distribution with parameters *mu* and *kappa*.

Samples from a von Mises distribution represent randomly-chosen angles clustered around a mean angle. This distribution is an approximation to the wrapped normal distribution and is defined by

$$\mathrm{P}(x) = \frac{e^{\kappa \cos(x-\mu)}}{2\pi I_0(\kappa)}$$

where $I_0(\kappa)$ is the modified Bessel function of order 0.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property kappa**
Read-only property for the distribution's *kappa* parameter.

**property mu**
Read-only property for the distribution's *mu* parameter.

**sample**(*rand*) → float
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**Beta**(*alpha: float*, *beta: float*)

Represents a beta distribution with parameters *alpha* and *beta*.

The beta distribution is defined by

$$\mathrm{P}(x) = x^{\alpha-1}(1-x)^{\beta-1}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}$$

**property alpha**

Read-only property for the distribution's *alpha* parameter.

**as_dict**() → Dict

Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List

Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property beta**

Read-only property for the distribution's *beta* parameter.

**sample**(*rand*) → float

Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**Pareto**(*alpha: float*)

Represents a Pareto distribution with shape parameter *alpha* and minimum value 1.

The Pareto distribution has PDF

$$\mathrm{P}(x) = \frac{\alpha}{x^{\alpha+1}}$$

**property alpha**

Read-only property for the distribution's *alpha* parameter.

**as_dict**() → Dict

Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List

Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**sample**(*rand*) → float

Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**Weibull**(*alpha: float*, *beta: float*)

Represents a Weibull distribution with scale parameter *alpha* and shape parameter *beta*.

The distribution is defined by

$$\mathrm{P}(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{k-1} e^{-(x/\alpha)^k}$$

where $x \geq 0$.

**property alpha**
Read-only property for the distribution's *alpha* parameter.

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property beta**
Read-only property for the distribution's *beta* parameter.

**sample**(*rand*) → float
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**class** samplespace.distributions.**Gaussian**(*mu: float = 0.0*, *sigma: float = 1.0*)
Represents a Gaussian distribution with parameters *mu* and *sigma*.

The Gaussian, or Normal distribution is defined by

$$\mathrm{P}(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

**as_dict**() → Dict
Return a representation of the distribution as a dict.

The 'distribution' key is the name of the distribution, and the remaining keys are the distribution's kwargs.

**as_list**() → List
Return a representation of the distribution as a list.

The first element if the list is the name of the distribution, and the subsequent elements are ordered parameters.

**property mu**
Read-only property for the distribution's *mu* parameter.

**sample**(*rand*)
Sample from the distribution.

**Parameters** **rand** – The random generator used to generate the sample.

**property sigma**
Read-only property for the distribution's *sigma* parameter.

## 2.4 Serialization functions

samplespace.distributions.**distribution_from_list**(*as_list*)
Build a distribution using a list of parameters.

Expects a list of values in the same form return by a call to `Distribution.as_list()`; i.e. `['name', arg0, arg1, ...]`.

### Examples

```
>>> tri = Triangular(2.0, 5.0)
>>> tri_as_list = tri.as_list()
>>> tri_as_list
['triangular', 2.0, 5.0]
>>> new_tri = distribution_from_list(tri_as_list)
>>> assert tri == new_tri
```

**Raises**

- **KeyError** – if the distribution name is not recognized.
- **TypeError** – if the wrong number of arguments is given.

samplespace.distributions.**distribution_from_dict**(*as_dict*)
Build a distribution using a dictionary of keyword arguments.

Expects a dict in the same form as returned by a call to `Distribution.as_dict()`; i.e. `{'distribution':'name', 'arg0':'value', 'arg1':'value', ...}`.

### Examples

```
>>> gauss = Gaussian(0.8, 5.0)
>>> gauss_as_dict = gauss.as_dict()
>>> gauss_as_dict
{'distribution': 'gaussian', 'mu': 0.8, 'sigma': 5.0}
>>> new_gauss = distribution_from_dict(gauss_as_dict)
>>> assert gauss == new_gauss
```

**Raises**

- **KeyError** – if the distribution name is not recognized or provided.
- **TypeError** – if the wrong keyword arguments are provided.

**classmethod** samplespace.distribution.Distribution.**from_list**()
An alias for *distribution_from_list()*.

**classmethod** samplespace.distribution.Distribution.**from_dict**()
An alias for *distribution_from_dict()*.

## 2.5 Examples

Sampling from a distribution:

```
import random
import statistics

from samplespace.distributions import Gaussian, FiniteGeometric

gauss = Gaussian(15.0, 2.0)
samples = [gauss.sample(random) for _ in range(100)]
print('Mean:', statistics.mean(samples))
print('Standard deviation:', statistics.stdev(samples))

geo = FiniteGeometric(['one', 'two', 'three', 'four', 'five'], 0.7)
samples = [geo.sample(random) for _ in range(10)]
print(' '.join(samples))
```

Using other random generators:

```
from samplespace import distributions, RepeatableRandomSequence

exponential = distributions.Exponential(0.8)

rrs = RepeatableRandomSequence(seed=12345)
print([exponential.sample(rrs) for _ in range(5)])
# Will always print:
# [1.1959827296976795, 0.6056492468915003, 0.9155454941988664, 0.5653478889068511, 0.
↪6500080335986231]
```

Representations of distributions:

```
from samplespace.distributions import Pareto, DiscreteUniform, UniformCategorical

pareto = Pareto(2.5)
print('Pareto as dict:', pareto.as_dict())  # {'distribution': 'pareto', 'alpha': 2.5}
print('Pareto as list:', pareto.as_list())  # ['pareto', 2.5]

discrete = DiscreteUniform(3, 8)
print('Discrete uniform as dict:', discrete.as_dict())  # {'distribution':
↪'discreteuniform', 'min_val': 3, 'max_val': 8}
print('Discrete uniform as list:', discrete.as_list())  # ['discreteuniform', 3, 8]

cat = UniformCategorical(['string', 4, {'a':'dict'}])
print('Uniform categorical as dict:', cat.as_dict())  # {'distribution':
↪'uniformcategorical', 'population': ['string', 4, {'a': 'dict'}]}
print('Uniform categorical as list:', cat.as_list())  # ['uniformcategorical', [
↪'string', 4, {'a': 'dict'}]]
```

Storing distributions as in config files as lists:

```
import random
from samplespace import distributions

...

skeleton_config = {
```

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```
    'name': 'Skeleton',
    'starting_hp': ['gaussian', 50.0, 5.0],
    'coins_dropped': ['geometric', 0.8, True],
}

...

class Skeleton(object):
    def __init__(self, name, starting_hp, coins_dropped_dist):
        self.name = name
        self.starting_hp = starting_hp
        self.coins_dropped_dist = coins_dropped_dist

    def drop_coins(self):
        return self.coins_dropped_dist.sample(random)

...

class SkeletonFactory(object):

    def __init__(self, config):
        self.name = config['name']
        self.starting_hp_dist = distributions.distribution_from_list(config['starting_
↪hp'])
        self.coins_dropped_dist = distributions.distribution_from_list(config['coins_
↪dropped'])

    def make_skeleton(self):
        return Skeleton(
            self.name,
            int(self.starting_hp_dist.sample(random)),
            self.coins_dropped_dist)
```

Storing distributions in config files as dictionaries:

```
from samplespace import distributions, RepeatableRandomSequence

city_config = {
    "building_distribution": {
        "distribution": "weightedcategorical",
        "items": [
            ["house", 0.2],
            ["store", 0.4],
            ["tree", 0.8],
            ["ground", 5.0]
        ]
    }
}

rrs = RepeatableRandomSequence()
building_dist = distributions.distribution_from_dict(city_config['building_
↪distribution'])

buildings = [[building_dist.sample(rrs) for col in range(20)] for row in range(5)]

for row in buildings:
    for building_type in row:
```

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```
        if building_type == 'house':
            print('H', end='')
        elif building_type == 'store':
            print('S', end='')
        elif building_type == 'tree':
            print('T', end='')
        else:
            print('.', end='')
    print()
```

CHAPTER

# THREE

# SAMPLESPACE.ALGORITHMS - GENERAL SAMPLING ALGORITHMS

This module implements several general-purpose sampling algorithms.

samplespace.algorithms.**sample_discrete_roulette**(*randfloat: Callable[], float]*, *cum_weights: Sequence[float]*) → int

Sample from a given discrete distribution given its cumulative weights, using binary search / the roulette wheel selection algorithm.

**Parameters**

- **randfloat** (*Callable[[], float]*) – A function returning a random float in [0.0, 1.0), e.g. `random.random()`. Will only be called once.
- **cum_weights** (*Sequence[float]*) – The list of cumulative weights. These do not need to be normalized, so *cum_weights[-1]* does not necessarily have to be 1.0.

**Returns** An index into the population from 0 to `len(cum_weights) - 1`.

**class** samplespace.algorithms.**AliasTable**(*probability: Sequence[float]*, *alias: Sequence[int]*)

Sample from a given discrete distribution given its relative weights, using the alias table algorithm.

Alias tables are slow to construct, but offer increased sampling speed compared to the roulette wheel algorithm.

Construct a table using *from_weights()*.

**probability**

The probability row of the table

**Type** List[float]

**alias**

The alias row of the table

**Type** List[int]

**classmethod from_weights**(*weights: Sequence[float]*)

Construct an alias table using a list of relative weights.

The provided weights need not sum to 1.0.

**sample**(*randbelow: Callable[[int], int]*, *randchance: Callable[[float], bool]*) → int

Sample from the alias table.

**Parameters**

- **randbelow** (*Callable[[int], int]*) – A function returning a random int in [0, *arg*), e.g. `random.randrange()`. Will only be called once per sample.
- **randchance** (*Callable[[float], bool]*) – A function returning `True` with chance *arg* and `False` otherwise, e.g. `lambda arg: random.random() < arg`. Will only be called once per sample.

**Returns** An index into the population from 0 to `len(weights) - 1`.

## 3.1 Examples

Sampling from a discrete categorical distribution using the Roulette Wheel Selection algorithm:

```
import random
import itertools
from samplespace import algorithms


population = 'abcde'
weights = [0.1, 0.4, 0.2, 0.3, 0.5]

cum_weights = list(itertools.accumulate(weights))
indices = [algorithms.sample_discrete_roulette(random.random, cum_weights)
           for _ in range(25)]  # [0, 4, 4, ...]
samples = [population[index] for index in indices]  # ['a', 'e', 'e', ...]
```

Sampling from a discrete categorical distribution using the Alias Table algorithm and a repeatable sequence:

```
from samplespace import algorithms, RepeatableRandomSequence

population = 'abcde'
weights = [0.1, 0.4, 0.2, 0.3, 0.5]

rrs = RepeatableRandomSequence(seed=12345)
at = algorithms.AliasTable.from_weights(weights)
indices = [at.sample(rrs.randrange, rrs.chance) for _ in range(25)]
samples = [population[index] for index in indices]  # ['e', 'e', 'c', ...]

# Note that rrs.index == 50 at this point, since two random values
# were required for each sample.

# It is also possible to use AliasTable within a cascade:
rrs.reset()
indices = [0] * 25
for i in range(len(indices)):
    with rrs.cascade():
        indices[i] = at.sample(rrs.randrange, rrs.chance)
samples = [population[index] for index in indices]  # ['e', 'd', 'b', ...]

# Because cascades were used, rrs.index == 25.
# Note that the values produced are different than the previous
# attempt, because a different number of logical samples were made.
```

CHAPTER

FOUR

# SAMPLESPACE.PYYAML_SUPPORT - YAML SERIALIZATION SUPPORT

When enabled, this module provides YAML serialization support for classes in *samplespace.repeatablerandom*, *samplespace.distributions*, and *samplespace.algorithms*.

The `yaml` module provided by PyYaml is required to use this module, and an exception will be thrown if it is not available.

**Tip:** Once the module is imported, *enable_yaml_support()* must be called to enable YAML support.

samplespace.pyyaml_support.**enable_yaml_support**(*_force=False*)
Add YAML serialization support. This function only needs to be called once per application.

## 4.1 Examples

Repeatable random sequence:

```
>>> import yaml
>>> from samplespace import RepeatableRandomSequence
>>> import samplespace.pyyaml_support
>>> samplespace.pyyaml_support.enable_yaml_support()
>>>
>>> rrs = RepeatableRandomSequence(seed=678)
>>> [rrs.randrange(10) for _ in range(5)]
[7, 7, 0, 8, 3]
>>>
>>> # Serialize the sequence as YAML
...
>>> as_yaml = yaml.dump(rrs)
>>> as_yaml
'!samplespace.rrs\nhash_input: s1enBV+SSXk=\nindex: 5\nseed: 678\n'
>>>
>>> # Generate some random values to compare against later
...
>>> [rrs.randrange(10) for _ in range(5)]
[0, 5, 1, 3, 9]
>>> [rrs.randrange(10) for _ in range(5)]
[7, 1, 1, 0, 5]
>>> [rrs.randrange(10) for _ in range(5)]
```

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```
[2, 9, 1, 4, 8]
>>>
>>> # Restore the saved sequence
...
>>> rrs2 = yaml.load(as_yaml, Loader=yaml.FullLoader)
>>>
>>> # Verify that values match those at time of serialization
...
>>> [rrs2.randrange(10) for _ in range(5)]
[0, 5, 1, 3, 9]
>>> [rrs2.randrange(10) for _ in range(5)]
[7, 1, 1, 0, 5]
>>> [rrs2.randrange(10) for _ in range(5)]
[2, 9, 1, 4, 8]
```

Distributions:

```
>>> import yaml
>>> from samplespace import distributions
>>> import samplespace.pyyaml_support
>>> samplespace.pyyaml_support.enable_yaml_support()
>>>
>>> gamma = distributions.Gamma(5.0, 3.0)
>>> gamma_as_yaml = yaml.dump(gamma)
>>> print(gamma_as_yaml)
!samplespace.distribution
alpha: 5.0
beta: 3.0
distribution: gamma
>>> assert yaml.load(gamma_as_yaml, Loader=yaml.FullLoader) == gamma
>>>
>>> zipf = distributions.Zipf(0.9, 10)
>>> zipf_as_yaml = yaml.dump(zipf)
>>> print(zipf_as_yaml)
!samplespace.distribution
distribution: zipf
n: 10
s: 0.9
>>> assert yaml.load(zipf_as_yaml, Loader=yaml.FullLoader) == zipf
>>>
>>> wcat = distributions.WeightedCategorical(
...     population='abcde',
...     cum_weights=[0.1, 0.4, 0.6, 0.7, 1.1])
>>> wcat_as_yaml = yaml.dump(wcat)
>>> print(wcat_as_yaml)
!samplespace.distribution
distribution: weightedcategorical
items:
- - a
  - 0.1
- - b
  - 0.30000000000000004
- - c
  - 0.19999999999999996
- - d
  - 0.09999999999999998
- - e
```

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```
  - 0.40000000000000013
>>> assert yaml.load(wcat_as_yaml, Loader=yaml.FullLoader) == wcat
```

Algorithms:

```
>>> import yaml
>>> from samplespace.algorithms import AliasTable
>>> import samplespace.pyyaml_support
>>> samplespace.pyyaml_support.enable_yaml_support()
>>>
>>> at = AliasTable.from_weights([0.1, 0.3, 0.5, 0.2, 0.6, 0.7])
>>> at.alias
[4, 5, 0, 5, 2, 4]
>>> at.probability
[0.25, 0.7499999999999998, 1.0, 0.5, 0.7499999999999991, 0.9999999999999996]
>>>
>>> at_as_yaml = yaml.dump(at)
>>> print(at_as_yaml)
!samplespace.aliastable
alias:
- 4
- 5
- 0
- 5
- 2
- 4
probability:
- 0.25
- 0.7499999999999998
- 1.0
- 0.5
- 0.7499999999999991
- 0.9999999999999996
>>> at2 = yaml.load(at_as_yaml, Loader=yaml.FullLoader)
>>> assert at2.alias == at.alias
>>> assert at2.probability == at.probability
```

CHAPTER

FIVE

# RANDOM GENERATOR QUALITY

`RepeatableRandomSequence` produces high-quality psuedo-random data regardless of seed or cascade size.

The script `tests/generate_random_bytes.py` can be used to generate files filled with random bytes for testing with external testing programs, or `tests/stream_random_bytes.py [seed]` can be used to stream an unlimited number of random bytes to stdout.

## 5.1 Randomness Test Results

Results from ENT:

```
$ python stream_random_bytes.py | head -c 8388608 | ent
Entropy = 7.999979 bits per byte.

Optimum compression would reduce the size
of this 8388608 byte file by 0 percent.

Chi square distribution for 8388608 samples is 244.76, and randomly
would exceed this value 66.64 percent of the times.

Arithmetic mean value of data bytes is 127.4945 (127.5 = random).
Monte Carlo value for Pi is 3.141415391 (error 0.01 percent).
Serial correlation coefficient is 0.000034 (totally uncorrelated = 0.0).
```

Results from Dieharder:

```
#=============================================================================#
#            dieharder version 3.31.1 Copyright 2003 Robert G. Brown          #
#=============================================================================#
        test_name   |ntup| tsamples |psamples|  p-value |Assessment
#=============================================================================#
   diehard_birthdays|   0|       100|     100|0.46260921|  PASSED
      diehard_operm5|   0|   1000000|     100|0.30499458|  PASSED
  diehard_rank_32x32|   0|     40000|     100|0.84557704|  PASSED
    diehard_rank_6x8|   0|    100000|     100|0.75986634|  PASSED
   diehard_bitstream|   0|   2097152|     100|0.26336497|  PASSED
        diehard_opso|   0|   2097152|     100|0.09991336|  PASSED
        diehard_oqso|   0|   2097152|     100|0.47106073|  PASSED
         diehard_dna|   0|   2097152|     100|0.09032458|  PASSED
diehard_count_1s_str|   0|    256000|     100|0.93473326|  PASSED
diehard_count_1s_byt|   0|    256000|     100|0.84493493|  PASSED
 diehard_parking_lot|   0|     12000|     100|0.33164281|  PASSED
    diehard_2dsphere|   2|      8000|     100|0.90268828|  PASSED
```

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(continued from previous page)

```
    diehard_3dsphere|   3|      4000|     100|0.87557333|  PASSED
     diehard_squeeze|   0|    100000|     100|0.75415145|  PASSED
        diehard_sums|   0|       100|     100|0.15694874|  PASSED
        diehard_runs|   0|    100000|     100|0.19158234|  PASSED
        diehard_runs|   0|    100000|     100|0.27969502|  PASSED
       diehard_craps|   0|    200000|     100|0.99326664|  PASSED
       diehard_craps|   0|    200000|     100|0.37802538|  PASSED
 marsaglia_tsang_gcd|   0|     40000|     100|0.44158442|  PASSED
 marsaglia_tsang_gcd|   0|     40000|     100|0.38455344|  PASSED
         sts_monobit|   1|    100000|     100|0.90249899|  PASSED
            sts_runs|   2|    100000|     100|0.77696296|  PASSED
          sts_serial|   1|    100000|     100|0.90249899|  PASSED
          sts_serial|   2|    100000|     100|0.59050254|  PASSED
          sts_serial|   3|    100000|     100|0.90871975|  PASSED
          sts_serial|   3|    100000|     100|0.99336098|  PASSED
          sts_serial|   4|    100000|     100|0.34637953|  PASSED
          sts_serial|   4|    100000|     100|0.23240191|  PASSED
          sts_serial|   5|    100000|     100|0.65698384|  PASSED
          sts_serial|   5|    100000|     100|0.20441284|  PASSED
          sts_serial|   6|    100000|     100|0.11455355|  PASSED
          sts_serial|   6|    100000|     100|0.10947486|  PASSED
          sts_serial|   7|    100000|     100|0.33236940|  PASSED
          sts_serial|   7|    100000|     100|0.90065107|  PASSED
          sts_serial|   8|    100000|     100|0.71691528|  PASSED
          sts_serial|   8|    100000|     100|0.72658614|  PASSED
          sts_serial|   9|    100000|     100|0.05947803|  PASSED
          sts_serial|   9|    100000|     100|0.35266839|  PASSED
          sts_serial|  10|    100000|     100|0.25645609|  PASSED
          sts_serial|  10|    100000|     100|0.96328452|  PASSED
          sts_serial|  11|    100000|     100|0.26614777|  PASSED
          sts_serial|  11|    100000|     100|0.75690153|  PASSED
          sts_serial|  12|    100000|     100|0.72460595|  PASSED
          sts_serial|  12|    100000|     100|0.59228401|  PASSED
          sts_serial|  13|    100000|     100|0.43108810|  PASSED
          sts_serial|  13|    100000|     100|0.39814551|  PASSED
          sts_serial|  14|    100000|     100|0.93222323|  PASSED
          sts_serial|  14|    100000|     100|0.10847133|  PASSED
          sts_serial|  15|    100000|     100|0.97030212|  PASSED
          sts_serial|  15|    100000|     100|0.74232610|  PASSED
          sts_serial|  16|    100000|     100|0.30293298|  PASSED
          sts_serial|  16|    100000|     100|0.74289769|  PASSED
         rgb_bitdist|   1|    100000|     100|0.52609114|  PASSED
         rgb_bitdist|   2|    100000|     100|0.35992730|  PASSED
         rgb_bitdist|   3|    100000|     100|0.80654719|  PASSED
         rgb_bitdist|   4|    100000|     100|0.84084274|  PASSED
         rgb_bitdist|   5|    100000|     100|0.54266728|  PASSED
         rgb_bitdist|   6|    100000|     100|0.04443687|  PASSED
         rgb_bitdist|   7|    100000|     100|0.22723549|  PASSED
rgb_minimum_distance|   4|     10000|    1000|0.23472614|  PASSED
    rgb_permutations|   5|    100000|     100|0.68681017|  PASSED
      rgb_lagged_sum|   0|   1000000|     100|0.57837513|  PASSED
     rgb_kstest_test|   0|     10000|    1000|0.52944830|  PASSED
```

## 5.2 Distribution Validity Tests

The scripts `tests/scripts/calculate_*_metrics.py` can be used to check that Repeatable Random Sequences produce values with the correct probability distributions.

Bear in mind that as limited samples are taken from each distribution, some false negatives may occur. If anomalous results are present, try re-running the scripts.

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# INDEX

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