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The Sage Development Team

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This file contains basic descriptive functions. Included are the mean, median, mode, moving average, standard deviation, and the variance. When calling a function on data, there are checks for functions already defined for that data type.

The mean function returns the arithmetic mean (the sum of all the members of a list, divided by the number of members). Further revisions may include the geometric and harmonic mean. The median function returns the number separating the higher half of a sample from the lower half. The mode returns the most common occurring member of a sample, plus the number of times it occurs. If entries occur equally common, the smallest of a list of the most common entries is returned. The moving_average is a finite impulse response filter, creating a series of averages using a user-defined number of subsets of the full data set. The std and the variance return a measurement of how far data points tend to be from the arithmetic mean.

Functions are available in the namespace stats, i.e. you can use them by typing stats.mean, stats.median, etc.

REMARK: If all the data you are working with are floating point numbers, you may find finance.TimeSeries helpful, since it is extremely fast and offers many of the same descriptive statistics as in the module.

AUTHOR:

• Andrew Hou (11/06/2009)

```
sage.stats.basic_stats.mean(v)
Return the mean of the elements of v.

We define the mean of the empty list to be the (symbolic) NaN, following the convention of MATLAB, Scipy, and R.

INPUT:

• v – a list of numbers

OUTPUT:

• a number

EXAMPLES:

sage: mean([pi, e])
1/2*pi + 1/2*e
sage: mean([])
NaN
sage: mean([I, sqrt(2), 3/5])
1/3*sqrt(2) + 1/3*I + 1/5
sage: mean([RIF(1.0103,1.0103), RIF(2)])
1.5051500000000000?
sage: mean(range(4))
(continues on next page)
```
sage.stats.basic_stats.median(v)

Return the median (middle value) of the elements of \( v \)

If \( v \) is empty, we define the median to be NaN, which is consistent with NumPy (note that R returns NULL). If \( v \) is comprised of strings, TypeError occurs. For elements other than numbers, the median is a result of sorted().

**INPUT:**

- \( v \) – a list

**OUTPUT:**

- median element of \( v \)

**EXAMPLES:**

```python
sage: median([1,2,3,4,5])
3
sage: median([e, pi])
1/2*pi + 1/2*e
sage: median(['sage', 'linux', 'python'])
'python'
sage: median([])
NaN
sage: class MyClass:
    ....:     def median(self):
    ....:         return 1
sage: stats.median(MyClass())
1
```

sage.stats.basic_stats.mode(v)

Return the mode of \( v \).

The mode is the list of the most frequently occuring elements in \( v \). If \( n \) is the most times that any element occurs in \( v \), then the mode is the list of elements of \( v \) that occur \( n \) times. The list is sorted if possible.

**Note:** The elements of \( v \) must be hashable.

**INPUT:**

- \( v \) – a list

**OUTPUT:**

- a list (sorted if possible)

**EXAMPLES:**

```python
sage: v = [1,2,4,1,6,2,6,7,1]
sage: mode(v)
[1]
sage: v.count(1)
3
```
sage: mode([])
[]
sage: mode([1, 2, 3, 4, 5])
[1, 2, 3, 4, 5]
sage: mode([3, 1, 2, 1, 2, 3])
[1, 2, 3]
sage: mode([0, 2, 7, 7, 13, 20, 2, 13])
[2, 7, 13]
sage: mode(['sage', 'four', 'I', 'three', 'sage', 'pi'])
['sage']
sage: class MyClass:
    ....: def mode(self):
    ....:     return [1]
sage: stats.mode(MyClass())
[1]

\texttt{sage.stats.basic_stats.moving\_average}(v, n)

Return the moving average of a list \( v \).

The moving average of a list is often used to smooth out noisy data.

If \( v \) is empty, we define the entries of the moving average to be NaN.

INPUT:

\begin{itemize}
    \item \( v \) – a list
    \item \( n \) – the number of values used in computing each average.
\end{itemize}

OUTPUT:

\begin{itemize}
    \item a list of length \( \text{len}(v) - n + 1 \), since we do not fabric any values
\end{itemize}

EXAMPLES:

sage: moving_average([1..10], 1)
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
sage: moving_average([1..10], 4)
[5/2, 7/2, 9/2, 11/2, 13/2, 15/2, 17/2]
sage: moving_average([], 1)
[]
sage: moving_average([pi, e, I, sqrt(2), 3/5], 2)
[1/2*pi + 1/2*e, 1/2*e + 1/2*I, 1/2*sqrt(2) + 1/2*I, 1/2*sqrt(2) + 3/10]

We check if the input is a time series, and if so use the optimized \texttt{simple\_moving\_average} method, but with (slightly different) meaning as defined above (the point is that the \texttt{simple\_moving\_average} on time series returns \( n \) values:

sage: a = finance.TimeSeries([1..10])
sage: stats.moving_average(a, 3)
[2.0000, 3.0000, 4.0000, 5.0000, 6.0000, 7.0000, 8.0000, 9.0000]
sage: stats.moving_average(list(a), 3)
[2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.0]

\texttt{sage.stats.basic\_stats.std}(v, bias=False)

Return the standard deviation of the elements of \( v \).
We define the standard deviation of the empty list to be NaN, following the convention of MATLAB, Scipy, and R.

INPUT:

- \( v \) – a list of numbers
- \texttt{bias} = \texttt{bool} (default: \texttt{False}); if \texttt{False}, divide by \( \text{len}(v) - 1 \) instead of \( \text{len}(v) \) to give a less biased estimator (sample) for the standard deviation.

OUTPUT:

- a number

EXAMPLES:

```python
sage: std([1..6], bias=True)
1/2*sqrt(35/3)
sage: std([1..6], bias=False)
sqrt(7/2)
sage: std([e, pi])
sqrt(1/2)*abs(pi - e)
sage: std([])
NaN
sage: std([I, sqrt(2), 3/5])
1/15*sqrt(1/2)*sqrt((10*sqrt(2) - 5*I - 3)^2 + (5*sqrt(2) - 10*I + 3)^2 + (5*sqrt(2) + 5*I - 6)^2)
sage: std([[RIF(1.0103, 1.0103), RIF(2)]])
0.6998235813403261?
sage: import numpy
sage: x = numpy.array([1,2,3,4,5])
sage: std(x, bias=False)
1.5811388300841898
sage: x = finance.TimeSeries([1..100])
sage: std(x)
29.011491975882016
```

```
sage.stats.basic_stats.variance(v, bias=False)
Return the variance of the elements of \( v \).

We define the variance of the empty list to be NaN, following the convention of MATLAB, Scipy, and R.

INPUT:

- \( v \) – a list of numbers
- \texttt{bias} = \texttt{bool} (default: \texttt{False}); if \texttt{False}, divide by \( \text{len}(v) - 1 \) instead of \( \text{len}(v) \) to give a less biased estimator (sample) for the standard deviation.

OUTPUT:

- a number

EXAMPLES:

```python
sage: variance([1..6])
7/2
sage: variance([1..6], bias=True)
35/12
sage: variance([e, pi])
1/2*(pi - e)^2
sage: variance([])

(continues on next page)
```
NaN

sage: variance([I, sqrt(2), 3/5])
1/450*(10*sqrt(2) - 5*I - 3)^2 + 1/450*(5*sqrt(2) - 10*I + 3)^2
+ 1/450*(5*sqrt(2) + 5*I - 6)^2
sage: variance([RIF(1.0103, 1.0103), RIF(2)])
0.4897530450000000?

sage: import numpy
sage: x = numpy.array([1,2,3,4,5])
sage: variance(x, bias=False)
2.5
sage: x = finance.TimeSeries([1..100])
sage: variance(x)
841.6666666666666
sage: variance(x, bias=True)
833.25

sage: class MyClass:
    ....: def variance(self, bias = False):
    ....:     return 1
sage: stats.variance(MyClass())
1

sage: class SillyPythonList:
    ....: def __init__(self):
    ....:     self.__list = [2, 4]
    ....: def __len__(self):
    ....:     return len(self.__list)
    ....: def __iter__(self):
    ....:     return self.__list.__iter__()
    ....: def mean(self):
    ....:     return 3
sage: R = SillyPythonList()

sage: variance(R)
2
sage: variance(R, bias=True)
1
This is a class for fast basic operations with lists of C ints. It is similar to the double precision TimeSeries class. It has all the standard C int semantics, of course, including overflow. It is also similar to the Python list class, except all elements are C ints, which makes some operations much, much faster. For example, concatenating two IntLists can be over 10 times faster than concatenating the corresponding Python lists of ints, and taking slices is also much faster.

AUTHOR:
• William Stein, 2010-03

```python
class sage.stats.intlist.IntList
    Bases: object
    A list of C int's.
    list()
    Return Python list version of self with Python ints as entries.
    EXAMPLES:
    sage: a = stats.IntList([1..15]); a
    [1, 2, 3, 4, 5 ... 11, 12, 13, 14, 15]
    sage: a.list()
    [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]
    sage: list(a) == a.list()  
    True
    sage: type(a.list()[0])
    <... 'int'>
```

```python
max(index=False)
Return the largest value in this time series. If this series has length 0 we raise a ValueError
INPUT:
• index – bool (default: False); if True, also return index of maximum entry.
OUTPUT:
• int – largest value
• int – index of largest value; only returned if index=True
EXAMPLES:
    sage: v = stats.IntList([1,-4,3,-2,-4,3])
    sage: v.max()
    3
    sage: v.max(index=True)
    (3, 2)
```
**min** *(index=False)*

Return the smallest value in this integer list. If this series has length 0 we raise a ValueError.

**INPUT:**

- **index** – bool (default: False); if True, also return index of minimal entry.

**OUTPUT:**

- float – smallest value
- integer – index of smallest value; only returned if index=True

**EXAMPLES:**

```python
sage: v = stats.IntList([1,-4,3,-2,-4])
sage: v.min()
-4
sage: v.min(index=True)
(-4, 1)
```

**plot** *(*args, **kwds)*

Return a plot of this IntList. This just constructs the corresponding double-precision floating point TimeSeries object, passing on all arguments.

**EXAMPLES:**

```python
sage: stats.IntList([3,7,19,-2]).plot()
Graphics object consisting of 1 graphics primitive
sage: stats.IntList([3,7,19,-2]).plot(color='red',pointsize=50,points=True)
Graphics object consisting of 1 graphics primitive
```

**plot_histogram** *(*args, **kwds)*

Return a histogram plot of this IntList. This just constructs the corresponding double-precision floating point TimeSeries object, and plots it, passing on all arguments.

**EXAMPLES:**

```python
sage: stats.IntList([1..15]).plot_histogram()
Graphics object consisting of 50 graphics primitives
```

**prod** ()

Return the product of the entries of self.

**EXAMPLES:**

```python
sage: a = stats.IntList([1..10]); a
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
sage: a.prod()
3628800
sage: factorial(10)
3628800
```

Note that there can be overflow:

```python
sage: a = stats.IntList([2^30, 2]); a
[1073741824, 2]
sage: a.prod()
-2147483648
```
sum()
Return the sum of the entries of self.

EXAMPLES:

```
sage: stats.IntList([1..100]).sum()
5050
```

Note that there can be overflow, since the entries are C ints:

```
sage: a = stats.IntList([2^30,2^30]); a
[1073741824, 1073741824]
sage: a.sum()
-2147483648
```

time_series()
Return TimeSeries version of self, which involves changing each entry to a double.

EXAMPLES:

```
sage: T = stats.IntList([-2,3,5]).time_series(); T
[-2.0000, 3.0000, 5.0000]
sage: type(T)
<... 'sage.finance.time_series.TimeSeries'>
```

`sage.stats.intlist.unpickle_intlist_v1(v, n)`
Version 1 unpickle method.

INPUT:

- v – a raw char buffer

EXAMPLES:

```
sage: v = stats.IntList([1,2,3])
sage: s = v.__reduce__()[1][0]
sage: type(s) == type(b'')
True
sage: sage.stats.intlist.unpickle_intlist_v1(s, 3)
[1, 2, 3]
sage: sage.stats.intlist.unpickle_intlist_v1(s+s,6)
[1, 2, 3, 1, 2, 3]
sage: sage.stats.intlist.unpickle_intlist_v1(b'',0)
[]
```
This is a complete pure-Cython optimized implementation of Hidden Markov Models. It fully supports Discrete, Gaussian, and Mixed Gaussian emissions.

The best references for the basic HMM algorithms implemented here are:

• Tapas Kanungo’s “Hidden Markov Models”
• Jackson’s HMM tutorial: http://personal.ee.surrey.ac.uk/Personal/P.Jackson/tutorial/

LICENSE: Some of the code in this file is based on reading Kanungo’s GPLv2+ implementation of discrete HMM’s, hence the present code must be licensed with a GPLv2+ compatible license.

AUTHOR:

• William Stein, 2010-03

class sage.stats.hmm.hmm.DiscreteHiddenMarkovModel
  Bases: sage.stats.hmm.hmm.HiddenMarkovModel

  A discrete Hidden Markov model implemented using double precision floating point arithmetic.

INPUT:

• A – a list of lists or a square N x N matrix, whose (i,j) entry gives the probability of transitioning from state i to state j.
• B – a list of N lists or a matrix with N rows, such that B[i,k] gives the probability of emitting symbol k while in state i.
• pi – the probabilities of starting in each initial state, i.e., pi[i] is the probability of starting in state i.
• emission_symbols – None or list (default: None); if None, the emission_symbols are the ints [0..N-1], where N is the number of states. Otherwise, they are the entries of the list emissions_symbols, which must all be hashable.
• normalize –bool (default: True); if given, input is normalized to define valid probability distributions, e.g., the entries of A are made nonnegative and the rows sum to 1, and the probabilities in pi are normalized.

EXAMPLES:

```
sage: m = hmm.DiscreteHiddenMarkovModel([[0.4,0.6],[0.1,0.9]], [[0.1,0.9],[0.5,0.5]]); m
Discrete Hidden Markov Model with 2 States and 2 Emissions
Transition matrix:
[0.4 0.6]
[0.1 0.9]
Emission matrix:
[0.1 0.9]
[0.5 0.5]
```


Initial probabilities: [0.5000, 0.5000]

sage: m.log_likelihood([0,1,0,1,0,1])
-4.66693474691329...
sage: m.viterbi([0,1,0,1,0,1])
([1, 1, 1, 1, 1, 1], -5.378832842208748)
sage: m.baum_welch([0,1,0,1,0,1])
(0.0, 22)
sage: m
# rel tol 1e-10
Discrete Hidden Markov Model with 2 States and 2 Emissions
Transition matrix:
[1.0134345614745788e-70 1.0]
[ 1.0 3.9974352713558623e-19]
Emission matrix:
[ 7.380221566254936e-54 1.0]
[ 1.0 3.9974352626002193e-19]
Initial probabilities: [0.0000, 1.0000]
sage: m.sample(10)
[0, 1, 0, 1, 0, 1, 0, 1, 0, 1]
sage: m.graph().plot()
Graphics object consisting of 6 graphics primitives

A 3-state model that happens to always outputs ‘b’:

sage: m = hmm.DiscreteHiddenMarkovModel([[1/3]*3]*3, [[0,1,0]]*3, [1/3]*3, ['a','b →','c'])
sage: m.sample(10)
['b', 'b', 'b', 'b', 'b', 'b', 'b', 'b', 'b', 'b']

baum_welch (obs, max_iter=100, log_likelihood_cutoff=0.0001, fix_emissions=False)
Given an observation sequence obs, improve this HMM using the Baum-Welch algorithm to increase the probability of observing obs.

INPUT:

• obs – list of emissions
• max_iter – integer (default: 100) maximum number of Baum-Welch steps to take
• log_likelihood_cutoff – positive float (default: 1e-4); the minimal improvement in likelihood with respect to the last iteration required to continue. Relative value to log likelihood.
• fix_emissions – bool (default: False); if True, do not change emissions when updating

OUTPUT:

• changes the model in places, and returns the log likelihood and number of iterations.

EXAMPLES:

sage: m = hmm.DiscreteHiddenMarkovModel([[0.1,0.9], [0.9,0.1]], [[.5,.5], [.2,.8]])
sage: m.baum_welch([1,0]*20, log_likelihood_cutoff=0)
(0.0, 4)
sage: m
# rel tol 1e-14
Discrete Hidden Markov Model with 2 States and 2 Emissions
Transition matrix:
[1.3515269707707603e-51 1.0]
[ 1.0 0.0]
Emission matrix:
The following illustrates how Baum-Welch is only a local optimizer, i.e., the above model is far more likely to produce the sequence \([1,0]^{*20}\) than the one we get below:

```python
sage: m = hmm.DiscreteHiddenMarkovModel([[0.5,0.5],[0.5,0.5]], [[.5,.5],[.5,.5]])
sage: m.baum_welch([1,0]*20, log_likelihood_cutoff=0)
(-27.725887222397784, 1)
sage: m
Discrete Hidden Markov Model with 2 States and 2 Emissions
Transition matrix:
[0.5 0.5]
[0.5 0.5]
Emission matrix:
[0.5 0.5]
[0.5 0.5]
Initial probabilities: [0.5000, 0.5000]
```

We illustrate fixing emissions:

```python
sage: m = hmm.DiscreteHiddenMarkovModel([[0.1,0.9],[0.9,0.1]], [[.5,.5],[.2,.8]])
sage: set_random_seed(0); v = m.sample(100)
sage: m.baum_welch(v,fix_emissions=True)
(-66.98630856918774, 100)
sage: m.emission_matrix()
[0.5 0.5]
[0.2 0.8]
sage: m = hmm.DiscreteHiddenMarkovModel([[0.1,0.9],[0.9,0.1]], [[.5,.5],[.2,.8]])
sage: m.baum_welch(v)
(-66.782360659293..., 100)
sage: m.emission_matrix()  # rel tol le-14
[ 0.5303085748626447 0.46969142513735535]
[ 0.2909775555173978 0.7090224449826023]
```

### emission_matrix()

Return the matrix whose \(i\)-th row specifies the emission probability distribution for the \(i\)-th state.

More precisely, the \(i,j\) entry of the matrix is the probability of the Markov model outputting the \(j\)-th symbol when it is in the \(i\)-th state.

**OUTPUT:**

- a Sage matrix with real double precision (RDF) entries.

**EXAMPLES:**

```python
sage: m = hmm.DiscreteHiddenMarkovModel([[0.4,0.6],[0.1,0.9]], [[0.1,0.9],[0.5,0.5]])
sage: E = m.emission_matrix(); E
[0.1 0.9]
[0.5 0.5]
```

The returned matrix is mutable, but changing it does not change the transition matrix for the model:
generate_sequence(length, starting_state=None)

Return a sample of the given length from this HMM.

INPUT:

- length -- positive integer
- starting_state -- int (or None); if specified then generate a sequence using this model starting with the given state instead of the initial probabilities to determine the starting state.

OUTPUT:

- an IntList or list of emission symbols
- IntList of the actual states the model was in when emitting the corresponding symbols

EXAMPLES:

In this example, the emission symbols are not set:

```
sage: set_random_seed(0)
sage: a = hmm.DiscreteHiddenMarkovModel([[0.1,0.9],[0.1,0.9]], [[1,0],[0,1]], →[0,1])
sage: a.generate_sequence(5)
([1, 0, 1, 1, 1], [1, 0, 1, 1, 1])
sage: list(a.generate_sequence(1000)[0]).count(0)
90
```

Here the emission symbols are set:

```
sage: set_random_seed(0)
sage: a = hmm.DiscreteHiddenMarkovModel([[0.5,0.5],[0.1,0.9]], [[1,0],[0,1]], →[0,1], ['up', 'down'])
sage: a.generate_sequence(5)
(['down', 'up', 'down', 'down', 'down'], [1, 0, 1, 1, 1])
```

Specify the starting state:

```
sage: set_random_seed(0); a.generate_sequence(5, starting_state=0)
(['up', 'up', 'down', 'down', 'down'], [0, 0, 1, 1, 1])
```

log_likelihood(obs, scale=True)

Return the logarithm of the probability that this model produced the given observation sequence. Thus the output is a non-positive number.

INPUT:

- obs -- sequence of observations
- scale -- boolean (default: True); if True, use rescaling to overoid loss of precision due to the very limited dynamic range of floats. You should leave this as True unless the obs sequence is very small.

EXAMPLES:
sage: m = hmm.DiscreteHiddenMarkovModel([[0.4,0.6],[0.1,0.9]], [[0.1,0.9],[0.5,0.5]], [(2,8)])
sage: m.log_likelihood([0, 1, 0, 1, 1, 0, 1, 0, 0, 0], scale=False)
-7.330130800937082

sage: m.log_likelihood([0, 1, 0, 1, 1, 0, 1, 0, 0, 0])
-7.330130800937082

sage: m.log_likelihood([])
0.0

sage: m = hmm.DiscreteHiddenMarkovModel([[0.4,0.6],[0.1,0.9]], [[0.1,0.9],[0.5,0.5]], [(2,8),('happy','sad')])
sage: m.log_likelihood(['happy','happy'])
-1.6565295199679506

sage: m.log_likelihood(['happy','sad'])
-1.473160294141552

Overflow from not using the scale option:

sage: m = hmm.DiscreteHiddenMarkovModel([[0.4,0.6],[0.1,0.9]], [[0.1,0.9],[0.5,0.5]], [(2,8)])
sage: m.log_likelihood([0,1]*1000, scale=True)
-1433.820666652728

sage: m.log_likelihood([0,1]*1000, scale=False)
-inf

**viterbi**(obs, log_scale=True)

Determine “the” hidden sequence of states that is most likely to produce the given sequence seq of observations, along with the probability that this hidden sequence actually produced the observation.

**INPUT:**

- seq – sequence of emitted ints or symbols
- log_scale – bool (default: True) whether to scale the sequence in order to avoid numerical overflow.

**OUTPUT:**

- list – “the” most probable sequence of hidden states, i.e., the Viterbi path.
- float – log of probability that the observed sequence was produced by the Viterbi sequence of states.

**EXAMPLES:**

sage: a = hmm.DiscreteHiddenMarkovModel([[0.1,0.9],[0.1,0.9]], [[0.9,0.1],[0.5,0.5]])
sage: a.viterbi([1,0,0,1,0,0,1,1])
([1, 0, 0, 1, ..., 0, 1, 1], -11.06245322477221...)

We predict the state sequence when the emissions are 3/4 and ‘abc’:

sage: a = hmm.DiscreteHiddenMarkovModel([[0.1,0.9],[0.1,0.9]], [[0.9,0.1],[0.5,0.5]], [3/4, 'abc'])

([0, 1, 1, 0, 0 ... 0, 0, 0, 0], -25.299405845367794)

Note that state 0 is common below, despite the model trying hard to switch to state 1:

([0, 1, 1, 0, 0 ... 0, 0, 0, 0], -25.299405845367794)
class sage.stats.hmm.hmm.HiddenMarkovModel
    Bases: object
    
    Abstract base class for all Hidden Markov Models.

graph (eps=0.001)
    Create a weighted directed graph from the transition matrix, not including any edge with a probability less
    than eps.

    INPUT:
    • eps – nonnegative real number

    OUTPUT:
    • a digraph

    EXAMPLES:

    sage: m = hmm.DiscreteHiddenMarkovModel([[.3,0,.7],[0,0,1],[.5,.5,0]], [[.5,.7,.2]*3, [1/3]*3)
    sage: G = m.graph(); G
    Looped digraph on 3 vertices
    sage: G.edges()
    [(0, 0, 0.3), (0, 2, 0.7), (1, 2, 1.0), (2, 0, 0.5), (2, 1, 0.5)]
    sage: G.plot()
    Graphics object consisting of 11 graphics primitives

initial_probabilities ()
    Return the initial probabilities, which as a TimeSeries of length N, where N is the number of states of the
    Markov model.

    EXAMPLES:

    sage: m = hmm.DiscreteHiddenMarkovModel([[0.4,0.6],[0.1,0.9]], [[0.1,0.9],[0.5,0.5]], [.1,.9])
    sage: pi = m.initial_probabilities(); pi
    [0.2000, 0.8000]
    sage: type(pi)
    <... 'sage.finance.time_series.TimeSeries'>

    The returned time series is a copy, so changing it does not change the model.
    sage: pi[0] = .1; pi[1] = .9 sage: m.initial_probabilities() [0.2000, 0.8000]

    Some other models:

    sage: hmm.GaussianHiddenMarkovModel([[.1,.9],[.5,.5]], [(1,0), (-1,1)], [.1,.9]).initial_probabilities()
    [0.1000, 0.9000]
    sage: hmm.GaussianMixtureHiddenMarkovModel([[.9,.1],[.4,.6]], [(.4,(0,1)), (.6,(1,0.1))], [(1,(0,1))]], [.7,.3]).initial_probabilities()
    [0.7000, 0.3000]

sample (length, number=None, starting_state=None)
    Return number samples from this HMM of given length.

    INPUT:
    • length – positive integer
    • number – (default: None) if given, compute list of this many sample sequences
• **starting_state** – int (or None); if specified then generate a sequence using this model starting with the given state instead of the initial probabilities to determine the starting state.

**OUTPUT:**

• if number is not given, return a single TimeSeries.

• if number is given, return a list of TimeSeries.

**EXAMPLES:**

```
sage: set_random_seed(0)
sage: a = hmm.DiscreteHiddenMarkovModel([[0.1, 0.9], [0.1, 0.9]], [[1,0],[0,1]],
        →[0,1])
sage: print(a.sample(10, 3))
[0, 1, 1, 0, 1, 1, 0, 1, 1, 1], [1, 1, 0, 0, 1, 1, 1, 1, 1, 1], [1, 1, 1, 1, 0, 1, 1, 1, 1, 1]]
sage: a.sample(15)
[1, 1, 1, 0 ... 1, 1, 1, 1]  # more sequence
sage: a.sample(3, 1)
[[1, 1, 1]]
sage: list(a.sample(1000)).count(0)
88
```

If the emission symbols are set:

```
sage: set_random_seed(0)
sage: a = hmm.DiscreteHiddenMarkovModel([[0.5,0.5], [0.1,0.9]], [[0.5,.5], [.1,.9]],
        →[0,1], ['up', 'down'])
sage: a.sample(10)
['down', 'up', 'down', 'down', 'down', 'down', 'up', 'up', 'up', 'up']
```

Force a starting state:

```
sage: set_random_seed(0); a.sample(10, starting_state=0)
['up', 'up', 'down', 'down', 'down', 'down', 'up', 'up', 'up', 'up']
```

**transition_matrix()**

Return the state transition matrix.

**OUTPUT:**

• a Sage matrix with real double precision (RDF) entries.

**EXAMPLES:**

```
sage: M = hmm.DiscreteHiddenMarkovModel([[0.7,0.3], [0.9,0.1]], [[0.5,.5], [.1,.9]],
        →[0,1], [0.3,0.7])
sage: T = M.transition_matrix(); T
[0.7 0.3]
[0.9 0.1]
```

The returned matrix is mutable, but changing it does not change the transition matrix for the model:

```
sage: T[0,0] = .1; T[0,1] = .9
 sage: M.transition_matrix()
[0.7 0.3]
[0.9 0.1]
```

Transition matrices for other types of models:

sage: hmm.GaussianHiddenMarkovModel([[.1,.9],[.5,.5]], [(1,1), (-1,1)], [.5,.5]).transition_matrix()
[0.1 0.9]
[0.5 0.5]
sage: hmm.GaussianMixtureHiddenMarkovModel([[.9,.1],[.4,.6]], [[.4,(0,1)), (.6,(1,0.1))],[(1,(0,1))]], [.7,.3]).transition_matrix()
[0.9 0.1]
[0.4 0.6]

sage.stats.hmm.hmm.unpickle_discrete_hmm_v0 (A, B, pi, emission_symbols, name)
sage.stats.hmm.hmm.unpickle_discrete_hmm_v1 (A, B, pi, n_out, emission_symbols, emission_symbols_dict)

Return a DiscreteHiddenMarkovModel, restored from the arguments.

This function is used internally for unpickling.
CLASS sage.stats.hmm.chmm.GaussianHiddenMarkovModel
Bases: sage.stats.hmm.hmm.HiddenMarkovModel

GaussianHiddenMarkovModel(A, B, pi)
Gaussian emissions Hidden Markov Model.

INPUT:

• A – matrix; the N x N transition matrix
• B – list of pairs (mu,sigma) that define the distributions
• pi – initial state probabilities
• normalize –bool (default: True)

EXAMPLES:

We illustrate the primary functions with an example 2-state Gaussian HMM:

```
sage: m = hmm.GaussianHiddenMarkovModel([[.1,.9],[.5,.5]], [(1,1), (-1,1)], [.5,.5]); m
Gaussian Hidden Markov Model with 2 States
Transition matrix:
[0.1 0.9]
[0.5 0.5]
Emission parameters:
[(1.0, 1.0), (-1.0, 1.0)]
Initial probabilities: [0.5000, 0.5000]
```

We query the defining transition matrix, emission parameters, and initial state probabilities:

```
sage: m.transition_matrix()
[0.1 0.9]
[0.5 0.5]
sage: m.emission_parameters()
[(1.0, 1.0), (-1.0, 1.0)]
sage: m.initial_probabilities()
[0.5000, 0.5000]
```

We obtain a sample sequence with 10 entries in it, and compute the logarithm of the probability of obtaining his sequence, given the model:
We compute the Viterbi path, and probability that the given path of states produced obs:

```sage```
m.viterbi(obs)
```
([1, 0, 1, 0, 1, 1, 0, 1, 0, 1], -16.67738270170788)
```

We use the Baum-Welch iterative algorithm to find another model for which our observation sequence is more likely:

```sage```
m.baum_welch(obs)
```
(-10.6103334957397..., 14)
```

Notice that running Baum-Welch changed our model:

```sage```
m # rel tol 3e-14
Gaussian Hidden Markov Model with 2 States
Transition matrix:
[ 0.4154981366185841 0.584501863381416]
[ 0.9999993174253741 6.825746258991804e-07]
Emission parameters:
[(0.4178882427119503, 0.5173109664360919), (-1.5025208631331122, 0.5085512836055119)]
Initial probabilities: [0.0000, 1.0000]
```

**baum_welch** (obs, max_iter=500, log_likelihood_cutoff=0.0001, min_sd=0.01, fix_emissions=False, v=False)
Given an observation sequence obs, improve this HMM using the Baum-Welch algorithm to increase the probability of observing obs.

**INPUT:**
- obs – a time series of emissions
- max_iter – integer (default: 500) maximum number of Baum-Welch steps to take
- log_likelihood_cutoff – positive float (default: 1e-4); the minimal improvement in likelihood with respect to the last iteration required to continue. Relative value to log likelihood.
- min_sd – positive float (default: 0.01); when reestimating, the standard deviation of emissions is not allowed to be less than min_sd.
- fix_emissions – bool (default: False); if True, do not change emissions when updating

**OUTPUT:**
- changes the model in places, and returns the log likelihood and number of iterations.

**EXAMPLES:**
```sage```
m = hmm.GaussianHiddenMarkovModel([[.1,.9],[.5,.5]], [(1,.5), (-1,3)],[.1,.9])
m.log_likelihood([-2,-1,.1,0.1])
```
-8.858282215986275
We illustrate bounding the standard deviation below. Note that above we had different emission parameters when the min_sd was the default of 0.01:

```python
sage: m = hmm.GaussianHiddenMarkovModel([[.1,.9],[.5,.5]], [(1,.5), (-1,3)], \rightarrow[.1,.9])
sage: m.baum_welch([-2,-1,0.1], min_sd=1)
(-4.07939572755..., 32)
sage: m.emission_parameters()
[(-0.2663018798..., 1.0), (-1.99850979..., 1.0)]
```

We watch the log likelihoods of the model converge, step by step:

```python
sage: v = m.sample(10)
sage: stats.TimeSeries([m.baum_welch(v,max_iter=1)[0] \text{ for } \_ \text{ in range(len(v))}])
```

We illustrate fixing emissions:

```python
sage: m = hmm.GaussianHiddenMarkovModel([[.1,.9],[.9,.1]], [(1,2),(-1,.5)], [.3,.7])
sage: set_random_seed(0); v = m.sample(100)
sage: m.baum_welch(v, fix_emissions=True)
(-164.72944548204..., 23)
sage: m.emission_parameters()
[(1.0, 2.0), (-1.0, 0.5)]
sage: m = hmm.GaussianHiddenMarkovModel([[.1,.9],[.9,.1]], [(1,2),(-1,.5)], [.3,.7])
sage: m.baum_welch(v)
(-162.854370397998..., 49)
sage: m.emission_parameters() \# rel tol 3e-14
[(1.2722419172602375, 2.371368751761901), (-0.9486174675179113, 0.5762360385123765)]
```

**emission_parameters()**

Return the parameters that define the normal distributions associated to all of the states.

**OUTPUT:**

- a list B of pairs B[i] = (mu, std), such that the distribution associated to state i is normal with mean mu and standard deviation std.

**EXAMPLES:**
generate_sequence\((\text{length, starting\_state=}\text{None})\)

Return a sample of the given length from this HMM.

**INPUT:**

- `length` – positive integer
- `starting\_state` – int (or None); if specified then generate a sequence using this model starting with the given state instead of the initial probabilities to determine the starting state.

**OUTPUT:**

- an IntList or list of emission symbols
- TimeSeries of emissions

**EXAMPLES:**

```python
sage: m = hmm.GaussianHiddenMarkovModel([[.1,.9],[.5,.5]], [(1,.5), (-1,3)], [.1,.9])
sage: m.generate_sequence(5)
([[-3.0505, 0.5317, -4.5065, 0.6521, 1.0435], [1, 0, 1, 0, 1])
sage: m.generate_sequence(0)
([], [])
sage: m.generate_sequence(-1)
Traceback (most recent call last):
  ... ValueError: length must be nonnegative
```

Example in which the starting state is 0 (see trac ticket #11452):

```python
sage: set_random_seed(23); m.generate_sequence(2)
([0.6501, -2.0151], [0, 1])
```

Force a starting state of 1 even though as we saw above it would be 0:

```python
sage: set_random_seed(23); m.generate_sequence(2, starting\_state=1)
([[-3.1491, -1.0244], [1, 1])
```

Verify numerically that the starting state is 0 with probability about 0.1:

```python
sage: set_random_seed(0)
sage: v = [m.generate_sequence(1)[1][0] for i in range(10^5)]
sage: 1.0 + v.count(int(0)) / len(v)
0.0998200000000000
```

`log\_likelihood\((\text{obs})\)`

Return the logarithm of a continuous analogue of the probability that this model produced the given observation sequence.

Note that the “continuous analogue of the probability” above can be bigger than 1, hence the logarithm can be positive.

**INPUT:**

- `obs` – sequence of observations
• float

**EXAMPLES:**

```python
sage: m = hmm.GaussianHiddenMarkovModel([[.1,.9],[.5,.5]], [(1,.5), (-1,3)], →[[.1,.9]])
sage: m.log_likelihood([1,1,1])
-4.297880766072486
sage: set_random_seed(0); s = m.sample(20)
sage: m.log_likelihood(s)
-40.115714129484...
```

**viterbi** *(obs)*

Determine “the” hidden sequence of states that is most likely to produce the given sequence seq of observations, along with the probability that this hidden sequence actually produced the observation.

**INPUT:**

• seq – sequence of emitted ints or symbols

**OUTPUT:**

• list – “the” most probable sequence of hidden states, i.e., the Viterbi path.
• float – log of probability that the observed sequence was produced by the Viterbi sequence of states.

**EXAMPLES:**

We find the optimal state sequence for a given model:

```python
sage: m = hmm.GaussianHiddenMarkovModel([[0.5,0.5],[0.5,0.5]], [(0,1),(10,1)], →[0.5,0.5])
sage: m.viterbi([0,1,10,10,1])
((0, 0, 1, 1, 0), -9.0604285688230...)
```

Another example in which the most likely states change based on the last observation:

```python
sage: m = hmm.GaussianHiddenMarkovModel([[.1,.9],[.5,.5]], [(1,.5), (-1,3)], →[[.1,.9]])
sage: m.viterbi([-2,-1,.1,0.1])
((1, 1, 0, 1), -9.61823698847639...)
sage: m.viterbi([-2,-1,1,0.3])
((1, 1, 1, 0), -9.566023653378513)
```

**class** `sage.stats.hmm.chmm.GaussianMixtureHiddenMarkovModel`

**Bases:** `sage.stats.hmm.chmm.GaussianHiddenMarkovModel`

GaussianMixtureHiddenMarkovModel(A, B, pi)

Gaussian mixture Hidden Markov Model.

**INPUT:**

• A – matrix; the N x N transition matrix

• B – list of mixture definitions for each state. Each state may have a varying number of gaussians with selection probabilities that sum to 1 and encoded as (p,(mu,sigma))

• pi – initial state probabilities

• normalize –bool (default: True); if given, input is normalized to define valid probability distributions, e.g., the entries of A are made nonnegative and the rows sum to 1, and the probabilities in pi are normalized.
EXAMPLES:

```python
sage: A = [[0.5,0.5],[0.5,0.5]]
sage: B = [[(0.9,(0.0,1.0)), (0.1,(1,10000))],[(1,(1,1)), (0,(0,0.1))]]
sage: hmm.GaussianMixtureHiddenMarkovModel(A, B, [1,0])
Gaussian Mixture Hidden Markov Model with 2 States
Transition matrix:
[0.5 0.5]
[0.5 0.5]
Emission parameters:
[0.9*N(0.0,1.0) + 0.1*N(1.0,10000.0), 1.0*N(1.0,1.0) + 0.0*N(0.0,0.1)]
Initial probabilities: [1.0000, 0.0000]
```

**baum_welch** *(obs, max_iter=1000, log_likelihood_cutoff=1e-12, min_sd=0.01, fix_emissions=False)*

Given an observation sequence obs, improve this HMM using the Baum-Welch algorithm to increase the probability of observing obs.

**INPUT:**

- obs – a time series of emissions
- max_iter – integer (default: 1000) maximum number of Baum-Welch steps to take
- log_likelihood_cutoff – positive float (default: 1e-12); the minimal improvement in likelihood with respect to the last iteration required to continue. Relative value to log likelihood.
- min_sd – positive float (default: 0.01); when reestimating, the standard deviation of emissions is not allowed to be less than min_sd.
- fix_emissions – bool (default: False); if True, do not change emissions when updating

**OUTPUT:**

- changes the model in places, and returns the log likelihood and number of iterations.

**EXAMPLES:**

```python
sage: m = hmm.GaussianMixtureHiddenMarkovModel([[.9,.1], [.4,.6]], [[(.4,(0,1))], (.6,(1,0.1))], [(1,(0,1))], [.7,.3])
sage: set_random_seed(0); v = m.sample(10); v
[0.3576, -0.9365, 0.9449, -0.6957, 1.0217, 0.9644, 0.9987, -0.5950, -1.0219, 0.6477]
sage: m.log_likelihood(v)
-8.31408655939536...
sage: m.baum_welch(v)
(2.18905068682..., 15)
sage: m.log_likelihood(v)
2.18905068682...
sage: m  # rel tol 6e-12
Gaussian Mixture Hidden Markov Model with 2 States
Transition matrix:
[ 0.8746363339773399 0.12536366602266016]
[ 1.0 1.451685202290174e-40]
Emission parameters:
[0.500161629343*N(-0.812298726239,0.173329026744) + 0.499838370657*N(0.982433690378,0.029719932009), 1.0*N(0.503260056832,0.145881515324)]
Initial probabilities: [0.0000, 1.0000]
```

We illustrate bounding the standard deviation below. Note that above we had different emission parameters when the min_sd was the default of 0.01:
sage: m = hmm.GaussianMixtureHiddenMarkovModel([[.9,.1],[.4,.6]], [[(.4,(0, →1)), (.6,(1,0.1))],[(1,(1,0.1))]], [.7,.3])
sage: m.baum_welch(v, min_sd=1)
(-12.617885761692..., 1000)
sage: m.emission_parameters()
# rel tol 6e-12
[0.503545634447*N(0.200166509595,1.0) + 0.496454365553*N(0.0543433426535,1.0),
1.0*N(0.0,1.0)]

We illustrate fixing all emissions:

sage: m = hmm.GaussianMixtureHiddenMarkovModel([[.9,.1],[.4,.6]], [[(.4,(0, →1)), (.6,(1,0.1))],[(1,(1,0.1))]], [.7,.3])
sage: set_random_seed(0); v = m.sample(10)
sage: m.baum_welch(v, fix_emissions=True)
(-7.58656858997..., 36)
sage: m.emission_parameters()
[0.4*N(0.0,1.0) + 0.6*N(1.0,0.1), 1.0*N(0.0,1.0)]

emission_parameters()

Returns a list of all the emission distributions.

OUTPUT:

- list of Gaussian mixtures

EXAMPLES:

sage: m = hmm.GaussianMixtureHiddenMarkovModel([[.9,.1],[.4,.6]], [[(.4,(0, →1)), (.6,(1,0.1))],[(1,(1,0.1))]], [.7,.3])
sage: m.emission_parameters()
[0.4*N(0.0,1.0) + 0.6*N(1.0,0.1), 1.0*N(0.0,1.0)]
True
These distribution classes are designed specifically for HMM’s and not for general use in statistics. For example, they have fixed or non-fixed status, which only make sense relative to being used in a hidden Markov model.

AUTHOR:

- William Stein, 2010-03

```python
class sage.stats.hmm.distributions.DiscreteDistribution
    Bases: sage.stats.hmm.distributions.Distribution

class sage.stats.hmm.distributions.Distribution
    Bases: object

A distribution.

plot(*args, **kwds)
    Return a plot of the probability density function.

    INPUT:
    • args and kwds, passed to the Sage plot function

    OUTPUT:
    • a Graphics object

EXAMPLES:

sage: P = hmm.GaussianMixtureDistribution([(0.2,-10,.5),(.6,1,1),(.2,20,.5)])
sage: P.plot(-10,30)
Graphics object consisting of 1 graphics primitive

prob(x)
    The probability density function evaluated at x.

    INPUT:
    • x – object

    OUTPUT:
    • float

EXAMPLES:

This method must be defined in a derived class:
```python
import sage.stats.hmm.distributions

distribution = sage.stats.hmm.distributions.Distribution()
distribution.prob(0)
Traceback (most recent call last):
...
NotImplementedError

sample(n=None)
Return either a single sample (the default) or n samples from this probability distribution.

INPUT:
  • n – None or a positive integer

OUTPUT:
  • a single sample if n is 1; otherwise many samples

EXAMPLES:
This method must be defined in a derived class:
```
```python
import sage.stats.hmm.distributions
distribution = sage.stats.hmm.distributions.Distribution().sample()
Traceback (most recent call last):
...
NotImplementedError
```

```python
class sage.stats.hmm.distributions.GaussianDistribution
    Bases: sage.stats.hmm.distributions.Distribution
class sage.stats.hmm.distributions.GaussianMixtureDistribution
    Bases: sage.stats.hmm.distributions.Distribution

A probability distribution defined by taking a weighted linear combination of Gaussian distributions.

EXAMPLES:
```
sage: P = hmm.GaussianMixtureDistribution([(0.3, 1, 2), (0.7, -1, 1)]); P
0.3*N(1.0,2.0) + 0.7*N(-1.0,1.0)
sage: P[0]
(0.3, 1.0, 2.0)
sage: P.is_fixed()
False
sage: P.fix()
False
sage: P.is_fixed()
False
sage: P.unfix()
False
sage: P.is_fixed()
False
```

fix(i=None)
Set that this GaussianMixtureDistribution (or its ith component) is fixed when using Baum-Welch to update the corresponding HMM.

INPUT:
  • i – None (default) or integer; if given, only fix the i-th component

EXAMPLES:
sage: P = hmm.GaussianMixtureDistribution([(.2,-10,.5),(.6,1,1),(.2,20,.5)])
sage: P.is_fixed(); P.is_fixed()
False
sage: P.is_fixed(1)
True
sage: P.fix(); P.is_fixed()
True

is_fixed(i=None)

Return whether or not this GaussianMixtureDistribution is fixed when using Baum-Welch to update the corresponding HMM.

INPUT:

• i – None (default) or integer; if given, only return whether the i-th component is fixed

EXAMPLES:

sage: P = hmm.GaussianMixtureDistribution([(.2,-10,.5),(.6,1,1),(.2,20,.5)])
sage: P.is_fixed()
False
sage: P.is_fixed(0)
False
sage: P.fix(0); P.is_fixed()
False
sage: P.is_fixed(0)
True
sage: P.fix(); P.is_fixed()
True

prob(x)

Return the probability of x.

Since this is a continuous distribution, this is defined to be the limit of the p’s such that the probability of \([x,x+h]\) is p*h.

INPUT:

• x – float

OUTPUT:

• float

EXAMPLES:

sage: P = hmm.GaussianMixtureDistribution([(.2,-10,.5),(.6,1,1),(.2,20,.5)])
>>> P.prob(.5)
0.21123919605857971
>>> P.prob(-100)
0.0
>>> P.prob(20)
0.1595769121605731

prob_m(x, m)

Return the probability of x using just the m-th summand.

INPUT:

• x – float
• m – integer
OUTPUT:
  • float

EXAMPLES:

```sage
P = hmm.GaussianMixtureDistribution([(0.2,-10,.5),(.6,1,1),(0.2,20,.5)])
P.prob_m(.5, 0)
2.7608117680508...e-97
P.prob_m(.5, 1)
0.21123919605857971
P.prob_m(.5, 2)
0.0
```

**sample** *(n=None)*

Return a single sample from this distribution (by default), or if n>1, return a TimeSeries of samples.

INPUT:
  • n – integer or None (default: None)

OUTPUT:
  • float if n is None (default); otherwise a TimeSeries

EXAMPLES:

```sage
P = hmm.GaussianMixtureDistribution([(0.2,-10,.5),(.6,1,1),(0.2,20,.5)])
P.sample()
19.65824361087513
P.sample(1)
[-10.4683]
P.sample(5)
[-0.1688, -10.3479, 1.6812, 20.1083, -9.9801]
P.sample(0)
[]
P.sample(-3)
Traceback (most recent call last):
...
ValueError: n must be nonnegative
```

**unfix** *(i=None)*

Set that this GaussianMixtureDistribution (or its ith component) is not fixed when using Baum-Welch to update the corresponding HMM.

INPUT:
  • i – None (default) or integer; if given, only fix the i-th component

EXAMPLES:

```sage
P = hmm.GaussianMixtureDistribution([(0.2,-10,.5),(.6,1,1),(0.2,20,.5)])
P.fix(1); P.is_fixed(1)
True
P.unfix(1); P.is_fixed(1)
False
P.fix(); P.is_fixed()
True
P.unfix(); P.is_fixed()
False
```
sage.stats.hmm.distributions.unpickle_gaussian_mixture_distribution_v1(c0, c1, param, fixed)

Used in unpickling GaussianMixtureDistribution’s.

EXAMPLES:

```
sage: P = hmm.GaussianMixtureDistribution([(0.2,-10,.5),(.6,1,1),(.2,20,.5)])
sage: loads(dumps(P)) == P                 # indirect doctest
True
```
class sage.stats.hmm.util.HMM_Util
    Bases: object

    A class used in order to share cdef’s methods between different files.

    initial_probs_to_TimeSeries(pi, normalize)
    This function is used internally by the __init__ methods of various Hidden Markov Models.
    INPUT:
        • pi – vector, list, or TimeSeries
        • normalize – if True, replace negative entries by 0 and rescale to ensure that the sum of the entries in each row is equal to 1. If the sum of the entries in a row is 0, replace them all by 1/N.
    OUTPUT:
        • a TimeSeries of length N

    EXAMPLES:
    sage: import sage.stats.hmm.util
    sage: u = sage.stats.hmm.util.HMM_Util()
    sage: u.initial_probs_to_TimeSeries([0.1,0.2,0.9], True)
    [0.0833, 0.1667, 0.7500]
    sage: u.initial_probs_to_TimeSeries([0.1,0.2,0.9], False)
    [0.1000, 0.2000, 0.9000]

    normalize_probability_TimeSeries(T, i, j)
    This function is used internally by the Hidden Markov Models code.
    Replace entries of T[i:j] in place so that they are all nonnegative and sum to 1. Negative entries are replaced by 0 and T[i:j] is then rescaled to ensure that the sum of the entries in each row is equal to 1. If all entries are 0, replace them by 1/(j-i).
    INPUT:
        • T – a TimeSeries
        • i – nonnegative integer
        • j – nonnegative integer
    OUTPUT:
• T is modified

EXAMPLES:

```python
sage: import sage.stats.hmm.util
dsage: T = stats.TimeSeries([.1, .3, .7, .5])
sage: u = sage.stats.hmm.util.HMM_Util()
sage: u.normalize_probability_TimeSeries(T, 0, 3)
sage: T
[0.0909, 0.2727, 0.6364, 0.5000]
sage: u.normalize_probability_TimeSeries(T, 0, 4)
sage: T
[0.0606, 0.1818, 0.4242, 0.3333]
sage: abs(T.sum()-1) < 1e-8  # might not exactly equal 1 due to rounding
True
```

**state_matrix_to_TimeSeries** *(A, N, normalize)*

This function is used internally by the `__init__` methods of Hidden Markov Models to make a transition matrix from A.

**INPUT:**

- A – matrix, list, list of lists, or TimeSeries
- N – number of states
- normalize – if True, replace negative entries by 0 and rescale to ensure that the sum of the entries in each row is equal to 1. If the sum of the entries in a row is 0, replace them all by 1/N.

**OUTPUT:**

- a TimeSeries

**EXAMPLES:**

```python
sage: import sage.stats.hmm.util
dsage: u = sage.stats.hmm.util.HMM_Util()
sage: u.state_matrix_to_TimeSeries([ [.1, .7], [.3/7, 4/7] ], 2, True)
[0.1250, 0.8750, 0.4286, 0.5714]
sage: u.state_matrix_to_TimeSeries([ [.1, .7], [.3/7, 4/7] ], 2, False)
[0.1000, 0.7000, 0.4286, 0.5714]
```
This class realizes oracles which returns integers proportionally to \( \exp(-(x - c)^2/(2\sigma^2)) \). All oracles are implemented using rejection sampling. See `DiscreteGaussianDistributionIntegerSampler.__init__()` for which algorithms are available.

AUTHORS:


EXAMPLES:

We construct a sampler for the distribution \( D_{\sigma,c} \) with width \( \sigma = 3 \) and center \( c = 0 \):

```python
sage: from sage.stats.distributions.discrete_gaussian_integer import DiscreteGaussianDistributionIntegerSampler
sage: sigma = 3.0
sage: D = DiscreteGaussianDistributionIntegerSampler(sigma=sigma)
```

We ask for 100000 samples:

```python
sage: from six.moves import range
sage: n=100000; l = [D() for _ in range(n)]
```

These are sampled with a probability proportional to \( \exp(-x^2/18) \). More precisely we have to normalise by dividing by the overall probability over all integers. We use the fact that hitting anything more than 6 standard deviations away is very unlikely and compute:

```python
sage: bound = (6*sigma).floor()
sage: norm_factor = sum([exp(-x^2/(2*sigma^2)) for x in range(-bound,bound+1)])
sage: norm_factor
7.519...
```

With this normalisation factor, we can now test if our samples follow the expected distribution:

```python
sage: x=0; l.count(x), ZZ(round(n*exp(-x^2/(2*sigma^2))/norm_factor))
(13355, 13298)
sage: x=4; l.count(x), ZZ(round(n*exp(-x^2/(2*sigma^2))/norm_factor))
(5479, 5467)
sage: x=-10; l.count(x), ZZ(round(n*exp(-x^2/(2*sigma^2))/norm_factor))
(53, 51)
```

We construct an instance with a larger width:

```python
sage: from sage.stats.distributions.discrete_gaussian_integer import _
   ...DiscreteGaussianDistributionIntegerSampler
sage: sigma = 127
sage: D = DiscreteGaussianDistributionIntegerSampler(sigma=sigma, algorithm=
   ...'_uniform+online')
```

ask for 100000 samples:

```python
sage: from six.moves import range
sage: n=100000; l = [D() for _ in range(n)] # long time
```

and check if the proportions fit:

```python
sage: x=0; y=1; float(l.count(x))/l.count(y), exp(-x^2/(2*sigma^2))/exp(-y^2/
   .../(2*sigma^2)).n() # long time
(1.0, 1.00...)
```

```python
sage: x=0; y=-100; float(l.count(x))/l.count(y), exp(-x^2/(2*sigma^2))/exp(-y^2/
   .../(2*sigma^2)).n() # long time
(1.32..., 1.36...)
```

We construct a sampler with $c \% 1 = 0$:

```python
sage: from sage.stats.distributions.discrete_gaussian_integer import _
   ...DiscreteGaussianDistributionIntegerSampler
sage: sigma = 3
sage: D = DiscreteGaussianDistributionIntegerSampler(sigma=sigma, c=1/2)
```

```python
sage: from six.moves import range
sage: n=100000; l = [D() for _ in range(n)] # long time
sage: mean(l).n() # long time
0.486650000000000
```

REFERENCES:

• [DDLL2013]

class sage.stats.distributions.discrete_gaussian_integer.DiscreteGaussianDistributionInteger

   Bases: sage.structure.sage_object.SageObject

A Discrete Gaussian Sampler using rejection sampling.

   ____init____(sigma, c=0, tau=6, algorithm=None, precision='mp')

   Construct a new sampler for a discrete Gaussian distribution.

   INPUT:

   • sigma - samples $x$ are accepted with probability proportional to $\exp(-(x - c)/(2\sigma))$
   • c - the mean of the distribution. The value of $c$ does not have to be an integer. However, some
     algorithms only support integer-valued $c$ (default: 0)
   • tau - samples outside the range $([c] - [\sigma\tau], ..., [c] + [\sigma\tau])$ are considered to have probability zero.
     This bound applies to algorithms which sample from the uniform distribution (default: 6)
   • algorithm - see list below (default: "uniform+table" for $\sigma$ bounded by
     DiscreteGaussianDistributionIntegerSampler.table_cutoff and
     "uniform+online" for bigger $\sigma$)
   • precision - either "mp" for multi-precision where the actual precision used is taken from sigma
     or "dp" for double precision. In the latter case results are not reproducible. (default: "mp")

   ALGORITHMS:

Chapter 7. Discrete Gaussian Samplers over the Integers
• "uniform+table" - classical rejection sampling, sampling from the uniform distribution and accepted with probability proportional to $\exp\left(-\frac{x-c}{2\sigma}\right)$ where $\exp\left(-\frac{x-c}{2\sigma}\right)$ is precomputed and stored in a table. Any real-valued $c$ is supported.

• "uniform+logtable" - samples are drawn from a uniform distribution and accepted with probability proportional to $\exp\left(-\frac{x-c}{2\sigma}\right)$ where $\exp\left(-\frac{x-c}{2\sigma}\right)$ is computed using logarithmically many calls to Bernoulli distributions. See [DDLL2013] for details. Only integer-valued $c$ are supported.

• "uniform+online" - samples are drawn from a uniform distribution and accepted with probability proportional to $\exp\left(-\frac{x-c}{2\sigma}\right)$ where $\exp\left(-\frac{x-c}{2\sigma}\right)$ is computed in each invocation. Typically this is very slow. See [DDLL2013] for details. Any real-valued $c$ is accepted.

• "sigma2+logtable" - samples are drawn from an easily samplable distribution with $\sigma = k \cdot \sigma_2$ with $\sigma_2 = \sqrt{1/(2 \log 2)}$ and accepted with probability proportional to $\exp\left(-\frac{x-c}{2\sigma}\right)$ where $\exp\left(-\frac{x-c}{2\sigma}\right)$ is computed using logarithmically many calls to Bernoulli distributions (but no calls to $\exp$). See [DDLL2013] for details. Note that this sampler adjusts $\sigma$ to match $k \cdot \sigma_2$ for some integer $k$. Only integer-valued $c$ are supported.

EXAMPLES:

```python
sage: from sage.stats.distributions.discrete_gaussian_integer import *
sage: DiscreteGaussianDistributionIntegerSampler(3.0, algorithm="uniform+online")
Discrete Gaussian sampler over the Integers with sigma = 3.000000 and c = 0
sage: DiscreteGaussianDistributionIntegerSampler(3.0, algorithm="uniform+table")
Discrete Gaussian sampler over the Integers with sigma = 3.000000 and c = 0
```

Note that "sigma2+logtable" adjusts $\sigma$:

```python
sage: DiscreteGaussianDistributionIntegerSampler(3.0, algorithm="sigma2+logtable")
Discrete Gaussian sampler over the Integers with sigma = 3.397287 and c = 0
```

__call__()

Return a new sample.

EXAMPLES:

```python
sage: from sage.stats.distributions.discrete_gaussian_integer import *
sage: DiscreteGaussianDistributionIntegerSampler(3.0, algorithm="uniform+online")()
-3
sage: DiscreteGaussianDistributionIntegerSampler(3.0, algorithm="uniform+table")()
3
```

**algorithm**

**c**

**sigma**

**tau**
This class realizes oracles which returns polynomials in $\mathbb{Z}[x]$ where each coefficient is sampled independently with a probability proportional to $\exp\left(-\frac{(x - c)}{(2\sigma)}\right)$.

AUTHORS:

- Martin Albrecht, Robert Fitzpatrick, Daniel Cabracas, Florian Göpfert, Michael Schneider: initial version

EXAMPLES:

```python
sage: from sage.stats.distributions.discrete_gaussian_polynomial import DiscreteGaussianDistributionPolynomialSampler
sage: sigma = 3.0; n=1000
sage: l = [DiscreteGaussianDistributionPolynomialSampler(ZZ['x'], 64, sigma)() for _ in range(n)]
sage: l = [vector(f).norm().n() for f in l]
sage: mean(l), sqrt(64)*sigma
(23.83..., 24.0...)```

class `sage.stats.distributions.discrete_gaussian_polynomial.DiscreteGaussianDistributionPolynomialSampler`

Discrete Gaussian sampler for polynomials.

EXAMPLES:

```python
sage: from sage.stats.distributions.discrete_gaussian_polynomial import DiscreteGaussianDistributionPolynomialSampler
sage: DiscreteGaussianDistributionPolynomialSampler(ZZ['x'], 8, 3.0)() 3*x^7 + 3*x^6 - 3*x^5 - x^4 - 5*x^2 + 3
sage: gs = DiscreteGaussianDistributionPolynomialSampler(ZZ['x'], 8, 3.0)
[4*x^7 + 4*x^6 - 4*x^5 + 2*x^4 + x^3 - 4*x + 7, -5*x^6 + 4*x^5 - 3*x^3 + 4*x^2 + 3*x + 1]

__init__(P, n, sigma)

Construct a sampler for univariate polynomials of degree $n-1$ where coefficients are drawn independently with standard deviation $\sigma$.

INPUT:

- $P$ - a univariate polynomial ring over the Integers
- $n$ - number of coefficients to be sampled
• \( \sigma \) - coefficients \( x \) are accepted with probability proportional to \( \exp\left(-\frac{x}{2\sigma}\right) \).

If an object of type `sage.stats.distributions.discrete_gaussian_integer.DiscreteGaussianDistributionIntegerSampler` is passed, then this sampler is used to sample coefficients.

**EXAMPLES:**

```python
sage: from sage.stats.distributions.discrete_gaussian_polynomial import DiscreteGaussianDistributionPolynomialSampler
sage: DiscreteGaussianDistributionPolynomialSampler(ZZ['x'], 8, 3.0)()
3*x^7 + 3*x^6 - 3*x^5 - x^4 - 5*x^2 + 3
sage: gs = DiscreteGaussianDistributionPolynomialSampler(ZZ['x'], 8, 3.0)
sage: [gs() for _ in range(3)]
[4*x^7 + 4*x^6 - 4*x^5 + 2*x^4 + x^3 - 4*x + 7, -5*x^6 + 4*x^5 - 3*x^3 + 4*x^2 + x, 2*x^7 + 2*x^6 + 2*x^5 - x^4 - 2*x^2 + 3*x + 1]
```

__call__

Return a new sample.

**EXAMPLES:**

```python
sage: from sage.stats.distributions.discrete_gaussian_polynomial import DiscreteGaussianDistributionPolynomialSampler
sage: sampler = DiscreteGaussianDistributionPolynomialSampler(ZZ['x'], 8, 12.0)
sage: sampler()
8*x^7 - 11*x^5 - 19*x^4 + 6*x^3 - 34*x^2 - 21*x + 9
```
This file implements oracles which return samples from a lattice following a discrete Gaussian distribution. That is, if \( \sigma \) is big enough relative to the provided basis, then vectors are returned with a probability proportional to \( \exp(-|x - c|^2/(2\sigma^2)) \). More precisely lattice vectors in \( x \in \Lambda \) are returned with probability:

\[
\frac{\exp(-|x - c|^2/(2\sigma))}{\sum_{x \in \Lambda} \exp(-|x|^2/(2\sigma))}
\]

AUTHORS:


EXAMPLES:

```python
sage: from sage.stats.distributions.discrete_gaussian_lattice import DiscreteGaussianDistributionLatticeSampler
sage: D = DiscreteGaussianDistributionLatticeSampler(ZZ^10, 3.0)
sage: D(), D(), D()
((3, 0, -5, 0, -1, -3, 3, 3, -7, 2), (4, 0, 1, -2, -4, -4, 4, 0, 1, -4), (-3, 0, 4, 5, 0, 1, 3, 2, 0, -1))
```

class `sage.stats.distributions.discrete_gaussian_lattice.DiscreteGaussianDistributionLatticeSampler`

Bases: `sage.structure.sage_object.SageObject`

GPV sampler for Discrete Gaussians over Lattices.

EXAMPLES:

```python
sage: from sage.stats.distributions.discrete_gaussian_lattice import DiscreteGaussianDistributionLatticeSampler
sage: D = DiscreteGaussianDistributionLatticeSampler(ZZ^10, 3.0); D
Discrete Gaussian sampler with \( \sigma = 3.000000 \), \( c=(0, 0, 0, 0, 0, 0, 0, 0, 0, 0) \)

\( \) over lattice with basis

\[
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

(continues on next page)
We plot a histogram:

```
from sage.stats.distributions.discrete_gaussian_lattice import DiscreteGaussianDistributionLatticeSampler
import warnings
D = DiscreteGaussianDistributionLatticeSampler(identity_matrix(2), 3.0)
S = [D() for _ in range(2^12)]
l = [vector(v.list() + [S.count(v)]) for v in set(S)]
list_plot3d(l, point_list=True, interpolation='nn')
```

REFERENCES:

- [GPV2008]

```
__init__(B, sigma=1, c=None, precision=None)
Construct a discrete Gaussian sampler over the lattice \( \Lambda(B) \) with parameter \( \sigma \) and center \( c \).
```

INPUT:

- \( B \) – a basis for the lattice, one of the following:
  - an integer matrix,
  - an object with a \texttt{matrix()} method, e.g. \( \mathbb{Z}^n \), or
  - an object where \texttt{matrix(B)} succeeds, e.g. a list of vectors.
- \( \sigma \) – Gaussian parameter \( \sigma > 0 \).
- \( c \) – center \( c \), any vector in \( \mathbb{Z}^n \) is supported, but \( c \in \Lambda(B) \) is faster.
- \( \text{precision} \) – bit precision \( \geq 53 \).

EXAMPLES:

```
from sage.stats.distributions.discrete_gaussian_lattice import DiscreteGaussianDistributionLatticeSampler
n = 2; sigma = 3.0; m = 5000
D = DiscreteGaussianDistributionLatticeSampler(ZZ^n, sigma)
f = D.f
c = D._normalisation_factor_zz(); c
56.2162803067524

l = [D() for _ in range(m)]
v = vector(ZZ, n, (-3,-3))
l.count(v), ZZ(round(m*f(v)/c))
(39, 33)
target = vector(ZZ, n, (0,0))
l.count(target), ZZ(round(m*f(target)/c))
(116, 89)
```
sage: D = DiscreteGaussianDistributionLatticeSampler(qf, 3.0); D
Discrete Gaussian sampler with $\sigma = 3.000000$, $c=(0, 0, 0)$ over lattice with basis
\[
\begin{bmatrix}
2 & 1 & 1 \\
1 & 2 & 1 \\
1 & 1 & 2
\end{bmatrix}
\]
sage: D()
(0, 1, -1)

__call__()
Return a new sample.

EXAMPLES:

```
sage: from sage.stats.distributions.discrete_gaussian_lattice import DiscreteGaussianDistributionLatticeSampler
sage: D = DiscreteGaussianDistributionLatticeSampler(ZZ^3, 3.0, c=(1,0,0))
sage: L = [D() for _ in range(2^12)]
sage: abs(mean(L).n() - D.c)
0.08303258...
sage: D = DiscreteGaussianDistributionLatticeSampler(ZZ^3, 3.0, c=(1/2,0,0))
sage: L = [D() for _ in range(2^12)]  # long time
sage: mean(L).n() - D.c  # long time
(0.0607910156250000, -0.128417968750000, 0.0239257812500000)
```

c
Center $c$.

Samples from this sampler will be centered at $c$.

EXAMPLES:

```
sage: from sage.stats.distributions.discrete_gaussian_lattice import DiscreteGaussianDistributionLatticeSampler
sage: D = DiscreteGaussianDistributionLatticeSampler(ZZ^3, 3.0, c=(1,0,0)); D
Discrete Gaussian sampler with $\sigma = 3.000000$, $c=(1, 0, 0)$ over lattice with basis
\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\]
sage: D.c
(1, 0, 0)
```

static compute_precision(precision, sigma)
Compute precision to use.

INPUT:

- precision - an integer > 53 nor None.
- sigma - if precision is None then the precision of sigma is used.

EXAMPLES:
sage: from sage.stats.distributions.discrete_gaussian_lattice import DiscreteGaussianDistributionLatticeSampler
sage: DiscreteGaussianDistributionLatticeSampler.compute_precision(100, RR(3))
100
sage: DiscreteGaussianDistributionLatticeSampler.compute_precision(100, RealField(200)(3))
100
sage: DiscreteGaussianDistributionLatticeSampler.compute_precision(100, 3)
100
sage: DiscreteGaussianDistributionLatticeSampler.compute_precision(None, RR(3))
53
sage: DiscreteGaussianDistributionLatticeSampler.compute_precision(None, RealField(200)(3))
200
sage: DiscreteGaussianDistributionLatticeSampler.compute_precision(None, 3)
53

\textbf{sigma}

Gaussian parameter $\sigma$.

Samples from this sampler will have expected norm $\sqrt{n}\sigma$ where $n$ is the dimension of the lattice.

\textbf{EXAMPLES:}

```python
sage: from sage.stats.distributions.discrete_gaussian_lattice import DiscreteGaussianDistributionLatticeSampler
sage: D = DiscreteGaussianDistributionLatticeSampler(ZZ^3, 3.0, c=(1,0,0))
sage: D.sigma
3.0
```
### T-TEST USING R

The function `sage.stats.r.ttest(x, y, conf_level=0.95, **kw)` performs a T-test using R.

**Arguments:**
- `x, y` – vectors of same length
- `conf_level` – confidence level of the interval, $[0, 1)$ in percent

**Result:**
- Tuple: (p-value, R return object)

**Example:**

```python
sage: a, b = ttest([1,2,3,4,5],[1,2,3,3.5,5.121]); a
0.9410263720274274
```

---

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