

HMMPy

1.0

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Chapter 1

Namespace Index

1.1 Package List

Here are the packages with brief descriptions (if available):

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Chapter 2

Class Index

2.1 Class List

Here are the classes, structs, unions and interfaces with brief descriptions:

hmm.HMM	7
hmm.HMM_Classifier	9

Chapter 3

Namespace Documentation

3.1 Package hmm

Classes

- class [HMM_Classifier](#)
- class [HMM](#)

Functions

- def [symbol_index](#)
- def [forward](#)
- def [backward](#)
- def [viterbi](#)
- def [baum_welch](#)
- def [dishonest_casino_test](#)

3.1.1 Detailed Description

Python module for creating, training and applying hidden Markov models to discrete or continuous observations.
Author: Michael Hamilton, hamiltom@cs.colostate.edu
Theoretical concepts obtained from Rabiner, 1989.

3.1.2 Function Documentation

3.1.2.1 def `hmm.backward(hmm, Obs, c = None)`

Calculate the probability of a partial observation sequence from $t+1$ to T , given some state t .
Obs: observation sequence
hmm: model
c: the scaling coefficients from forward algorithm
returns: $B_t(i)$

3.1.2.2 def hmm.baum_welch (*hmm*, *Obs_seqs*, *args*)

EM algorithm to update Pi, A, and B for the HMM

:Parameters:

- 'hmm' - hmm model to train
- 'Obs_seqs' - list of observation sequences to train over

:Return:

a trained hmm

:Keywords:

- 'epochs' - number of iterations to perform EM, default is 20
- 'val_set' - validation data set, not required but recommended to prevent over-fitting
- 'updatePi' - flag to update initial state probabilities
- 'updateA' - flag to update transition probabilities, default is True
- 'updateB' - flag to update observation emission probabilities for discrete types, default is True
- 'scaling' - flag to scale probabilities (log scale), default is True
- 'graph' - flag to plot log-likelihoods of the training epochs, default is False
- 'normUpdate' - flag to use $1 / -(normed \log-likelihood)$ contribution for each observation sequence when updating model parameters, default is False
- 'fname' - file name to save plot figure, default is ll.eps
- 'verbose' - flag to print training times and log likelihoods for each training epoch, default is false

3.1.2.3 def hmm.forward (*hmm*, *Obs*, *scaling* = True)

Calculate the probability of an observation sequence, Obs, given the model, P(Obs|hmm).

Obs: observation sequence

hmm: model

returns: P(Obs|hmm)

3.1.2.4 def hmm.symbol_index (*hmm*, *Obs*)

Converts an observation symbol sequence into a sequence of indices for accessing distribution matrices.

3.1.2.5 def hmm.viterbi (*hmm*, *Obs*, *scaling* = True)

Calculate P(Q|Obs, hmm) and yield the state sequence Q* that maximizes this probability.

Obs: observation sequence

hmm: model

Chapter 4

Class Documentation

4.1 hmm.HMM Class Reference

Public Member Functions

- `def __init__`
- `def __repr__`

Public Attributes

- `N`
- `V`
- `M`
- `symbol_map`
- `A`
- `B`
- `F`
- `Pi`
- `Labels`

4.1.1 Detailed Description

Creates and maintains a hidden Markov model. This version assumes the every state can be reached DIRECTLY from any other state (ergodic). This, of course, excludes the start state. Hence the state transition matrix, `A`, must be $N \times N$. The observable symbol probability distributions are represented by an $N \times M$ matrix where M is the number of observation symbols.

$$A = \begin{bmatrix} |a_{11} & a_{12} & \dots & a_{1N}| \\ |a_{21} & a_{22} & \dots & a_{2N}| \\ |. & . & & .| \\ |. & . & & .| \\ |a_{N1} & a_{N2} & \dots & a_{NN}| \end{bmatrix} \qquad B = \begin{bmatrix} |b_{11} & b_{12} & \dots & b_{1M}| \\ |b_{21} & b_{22} & \dots & b_{2M}| \\ |. & . & & .| \\ |. & . & & .| \\ |b_{N1} & b_{N2} & \dots & b_{NM}| \end{bmatrix}$$

$a_{ij} = P(q_t = S_j | q_{t-1} = S_i)$ $b_{ik} = P(v_k \text{ at } t | q_t = S_i)$
where q_t is state at time t and v_k is k -th symbol of observation sequence

4.1.2 Member Function Documentation

4.1.2.1 `def hmm.HMM.__init__ (self, n_states = 1, args)`

:Keywords:

- 'n_states' - number of hidden states
- 'V' - list of all observable symbols
- 'A' - transition matrix
- 'B' - observable symbol probability distribution
- 'D' - dimensionality of continuous observations
- 'F' - Fixed emission probabilities for the given state (dict: i -> numpy.array([n_states]), where i is the state to hold fixed.

The documentation for this class was generated from the following file:

- `hmm.py`

4.2 hmm.HMM_Classifier Class Reference

Public Member Functions

- def `__init__`
- def `classify`
- def `add_pos_hmm`
- def `add_neg_hmm`

Public Attributes

- `neg_hmm`
- `pos_hmm`

4.2.1 Detailed Description

A binary hmm classifier that utilizes two hmms: one corresponding to the positive activity and one corresponding to the negative activity.

4.2.2 Member Function Documentation

4.2.2.1 def `hmm.HMM_Classifier.__init__ (self, args)`

:Keywords:

- `'neg_hmm'` - hmm corresponding to negative activity
- `'pos_hmm'` - hmm corresponding to positive activity

4.2.2.2 def `hmm.HMM_Classifier.add_neg_hmm (self, neg_hmm)`

Add the hmm corresponding to negative activity. Replaces current negative hmm, if it exists.

4.2.2.3 def `hmm.HMM_Classifier.add_pos_hmm (self, pos_hmm)`

Add the hmm corresponding to positive activity. Replaces current positive hmm, if it exists.

4.2.2.4 def `hmm.HMM_Classifier.classify (self, sample)`

Classification is performed by calculating the log odds for the positive activity. Since the hmms return a log-likelihood (due to scaling) of the corresponding activity, the difference of the two log-likelihoods is the log odds.

The documentation for this class was generated from the following file:

- `hmm.py`

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