

K-means clustering and vector quantization (`scipy.cluster.vq`)

K-means Clustering and Vector Quantization Module

Provides routines for k-means clustering, generating code books from k-means models, and quantizing vectors by comparing them to a code book.

The k-means algorithm takes as input the number of clusters to generate, `k`, and a set of observation vectors to cluster. It returns a list of centroids, one for each of the `k` clusters. An observation vector is classified with the cluster number or centroid index of the centroid closest to it.

A vector `v` belongs to cluster `i` if it is closer to centroid `i` than any other centroids. If `v` belongs to `i`, we say centroid `i` is the dominating centroid for `v`. Variants of k-means try to minimize distortion, which is defined as the sum of the distances between each observation vector and its assigned centroid. Each step of the k-means algorithm refines the choices of centroids to reduce distortion. The change in distortion is often used as a stopping criterion. If the change is lower than a threshold, the k-means algorithm is not making sufficient progress and terminates.

Since vector quantization is a natural application for k-means, information theory terminology is often used. The centroid index or cluster number is referred to as a “code” and the table mapping codes to centroids and vice versa is often referred to as a “code book”. The result of k-means, a list of centroids, can be used to quantize vectors. Quantization aims to find an encoding of vectors that reduces the expected distortion.

For example, suppose we wish to compress a 24-bit color image (each pixel is represented by one byte for red, one for green, and one for blue) and send it over the web. By using a smaller 8-bit encoding, we can reduce the amount of data by two thirds. Ideally, the colors for each encoding value should be chosen to minimize distortion of the color. Running k-means with `k=256` generates a code book of 256 possible 8-bit sequences. Instead of sending a 3-byte value for each pixel, the 8-bit centroid index (or code word) of the dominating centroid is sent. The code book is also sent over the wire so each 8-bit code can be translated back to a 24-bit pixel value representation. If the image is mostly blue ocean, we would expect many 24-bit blues to be represented by 8-bit codes. If it was an image of a human face, more flesh tone colors would be in the code book.

All routines expect `obs` to be a `M` by `N` array where the rows are the observation vectors. The codebook is a `k` by `N` array where the rows are the centroids. The code word is the centroid index `i`. The observation vectors and centroids have the same feature dimension.

- `whiten(obs)` – Normalize a group of observations so each feature has unit variance.
- `vq(obs,code_book)` – Calculate code book membership of a set of observation vectors.
- `kmeans(obs,k_or_guess,iter=20,thresh=1e-5)` – Clusters a set of observation vectors. Learns centroids with the k-means algorithm, trying to minimize distortion. A code book is generated and used to quantize vectors.
- `kmeans2` – A different implementation of k-means with more methods for initializing centroids. Uses maximum number of iterations as a stopping criterion and threshold as its stopping criterion.

`scipy.cluster.vq.whiten(obs)`
Normalize a group of observations on a per feature basis.

Before running k-means, it is beneficial to rescale each feature dimension of the observation set with whitening. Each feature is scaled by its standard deviation across all observations to give it unit variance.

Parameters:

obs : ndarray
Each row of the array is an observation. The columns are the features seen during each observation.

	#	f0	f1	f2	
obs =	[1.,	1.,	1.],	#0
	[2.,	2.,	2.],	#01
	[3.,	3.,	3.],	#02
	[4.,	4.,	4.]]	#03

XXX perhaps should have an axis variable here.

Returns:

result : ndarray
Contains the values in obs scaled by the standard deviation of each column.

Examples

```
>>> from numpy import array
>>> from scipy.cluster.vq import whiten
>>> features = array([[ 1.9,2.3,1.7],
...                  [ 1.5,2.5,2.2],
...                  [ 0.8,0.6,1.7]])
>>> whiten(features)
array([[ 3.41250074,  2.20300046,  5.88897275],
       [ 2.69407953,  2.39456571,  7.62102355],
       [ 1.43684242,  0.57469577,  5.88897275]])
```

`scipy.cluster.vq.vq(obs,code_book)`
Vector Quantization: assign codes from a code book to observations.

Assigns a code from a code book to each observation. Each observation vector in the `M` by `N` `obs` array is compared with the centroids in the `code_book` and assigned the code of the closest centroid.

The features in `obs` should have unit variance, which can be achieved by passing them through the `whiten` function. The code book is usually generated using the k-means algorithm or a different encoding algorithm.

Parameters:

obs : ndarray
Each row of the `NxM` array is an observation. The columns are the “features” seen during each observation, whitened first using the `whiten` function or something equivalent.

code_book : ndarray
The code book is usually generated using the k-means algorithm. Each row of the array holds a different centroid. The columns are the features of the code.

	#	f0	f1	f2	f3	
code_book =	[1.,	2.,	3.,	4.],	#c0
	[1.,	2.,	3.,	4.],	#c1
	[1.,	2.,	3.,	4.]]	#c2

Returns:

code : ndarray
A length N array holding the code book index for each observation.
dist : ndarray
The distortion (distance) between the observation and its nearest code.

Notes

This currently forces 32-bit math precision for speed. Anyone know of a situation where this undermines the accuracy of the algor

Examples

```
>>> from numpy import array
>>> from scipy.cluster.vq import vq
>>> code_book = array([[1.,1.,1.],
...                   [2.,2.,2.]])
>>> features = array([[ 1.9,2.3,1.7],
...                  [ 1.5,2.5,2.2],
...                  [ 0.8,0.6,1.7]])
>>> vq(features,code_book)
(array([1, 1, 0]), array([ 0.43588989,  0.73484692,  0.83066239]))
```

scipy.cluster.vq.**kmeans**(*obs, k_or_guess, iter=20, thresh=1.0000000000000001e-05*)

Performs k-means on a set of observation vectors forming k clusters. This yields a code book mapping centroids to codes and vice versa. The k-means algorithm adjusts the centroid cannot be made, i.e. the change in distortion since the last iteration is less than some threshold.

Parameters:

obs : ndarray
Each row of the M by N array is an observation vector. The columns are the features seen during each ob
must be whitened first with the whiten function.

k_or_guess : int or ndarray
The number of centroids to generate. A code is assigned to each centroid, which is also the row index
code_book matrix generated.
The initial k centroids are chosen by randomly selecting observations from the observation matrix. Alterna
array specifies the initial k centroids.

iter : int
The number of times to run k-means, returning the codebook with the lowest distortion. This argum
centroids are specified with an array for the k_or_guess paramter. This parameter does not represent the
the k-means algorithm.

thresh : float
Terminates the k-means algorithm if the change in distortion since the last k-means iteration is less than th

Returns:

codebook : ndarray
A k by N array of k centroids. The i'th centroid codebook[i] is represented with the code i. The centroid
represent the lowest distortion seen, not necessarily the globally minimal distortion.

distortion : float
The distortion between the observations passed and the centroids generated.

Seealso:

- kmeans2: a different implementation of k-means clustering with more methods for generating initial centrc
- whiten: must be called prior to passing an observation matrix to kmeans.

Examples

```
>>> from numpy import array
>>> from scipy.cluster.vq import vq, kmeans, whiten
>>> features = array([[ 1.9,2.3],
...                  [ 1.5,2.5],
...                  [ 0.8,0.6],
...                  [ 0.4,1.8],
...                  [ 0.1,0.1],
...                  [ 0.2,1.8],
...                  [ 2.0,0.5],
...                  [ 0.3,1.5],
...                  [ 1.0,1.0]])
>>> whitened = whiten(features)
>>> book = array((whitened[0],whitened[2]))
>>> kmeans(whitened,book)
(array([[ 2.3110306 ,  2.86287398],
        [ 0.93218041,  1.24398691]]), 0.85684700941625547)

>>> from numpy import random
>>> random.seed((1000,2000))
>>> codes = 3
>>> kmeans(whitened,codes)
(array([[ 2.3110306 ,  2.86287398],
        [ 1.32544402,  0.65607529],
        [ 0.40782893,  2.02786907]]), 0.5196582527686241)
```

scipy.cluster.vq.**kmeans2**(*data, k, iter=10, thresh=1.0000000000000001e-05, minit='random', missing='warn'*)

Classify a set of observations into k clusters using the k-means algorithm.

The algorithm attempts to minimize the Euclidian distance between observations and centroids. Several initialization methods are

Parameters:

data : ndarray
A M by N array of M observations in N dimensions or a length M array of M one-dimensional observations.

k : int or ndarray
The number of clusters to form as well as the number of centroids to generate. If minit initialization s
ndarray is given instead, it is interpreted as initial cluster to use instead.

iter : int
Number of iterations of the k-means algorithm to run. Note that this differs in meaning from the iters pa
function.

thresh : float
(not used yet).

	<div>minit : string</div> <div>Method for initialization. Available methods are ‘random’, ‘points’, ‘uniform’, and ‘matrix’: ‘random’: generate k centroids from a Gaussian with mean and variance estimated from the data. ‘points’: choose k observations (rows) at random from data for the initial centroids. ‘uniform’: generate k observations from the data from a uniform distribution defined by the data set (unsup ‘matrix’: interpret the k parameter as a k by M (or length k array for one-dimensional data) array of initial c</div>
Returns:	<div>centroid : ndarray</div> <div>A k by N array of centroids found at the last iteration of k-means.</div> <div>label : ndarray</div> <div>label[i] is the code or index of the centroid the i’t observation is closest to.</div>