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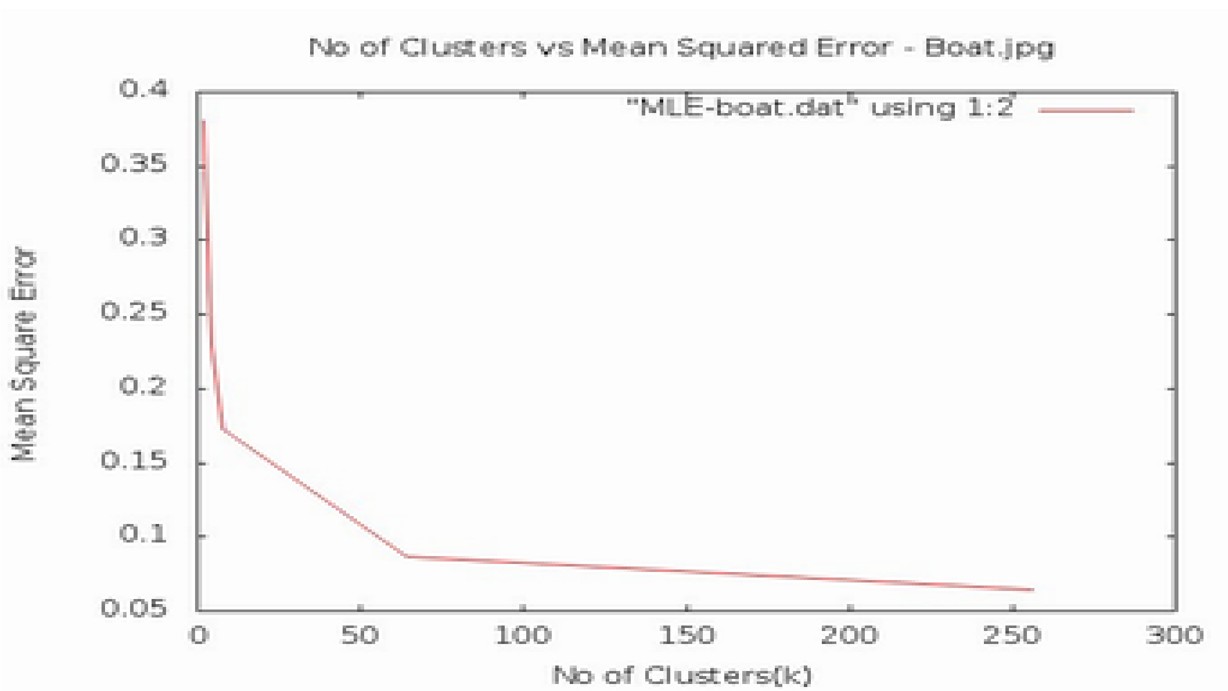
MACHINE LEARNING FALL 2012
ASSIGNMENT 4

Q.2.1:

Solution : It was observed that the mean square error decreases as no of clusters are increased.

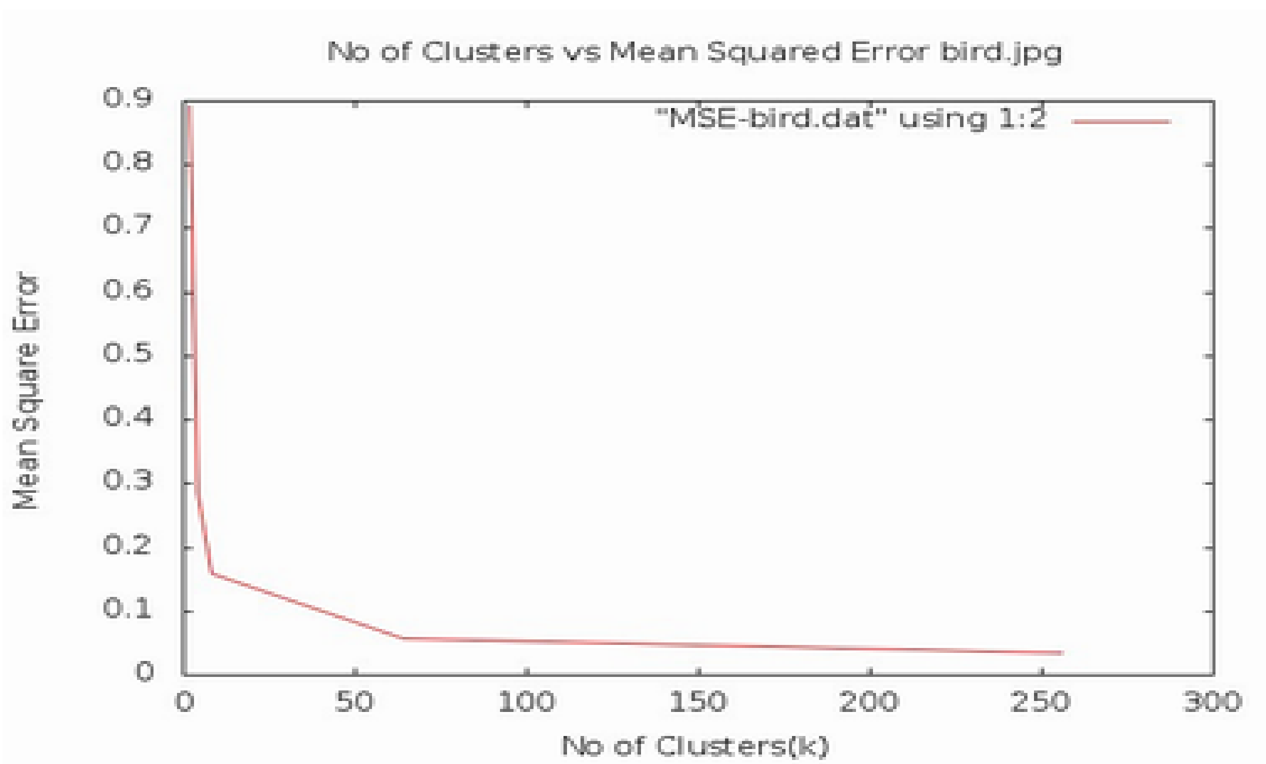
Boat.jpg

#k	#MSE
2	0.38082375762116
4	0.22940470568987
8	0.17266038633487
64	0.086587271120838
256	0.064565689512629



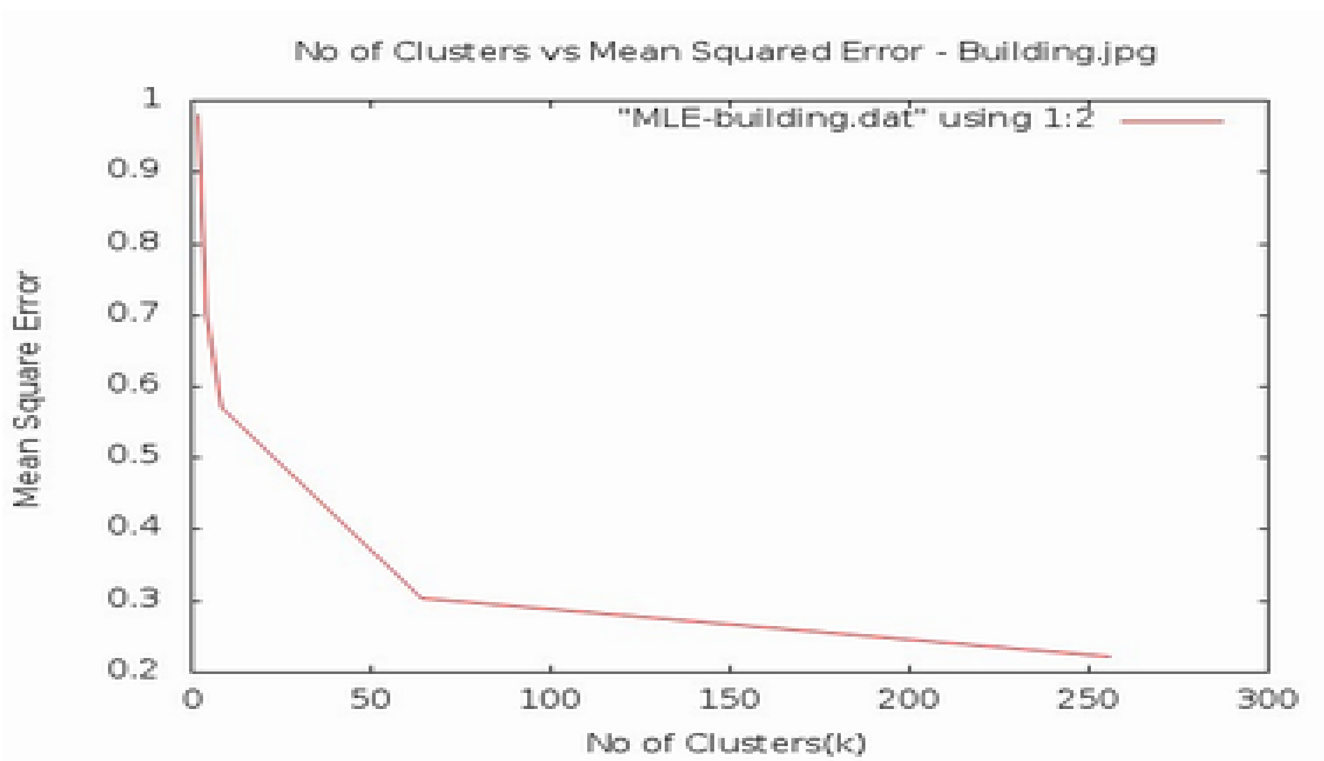
Bird.jpg

#k	#MSE
2	0.89156708234294
4	0.28674512147712
8	0.15875766585968
64	0.057471404206819
256	0.033733705099436



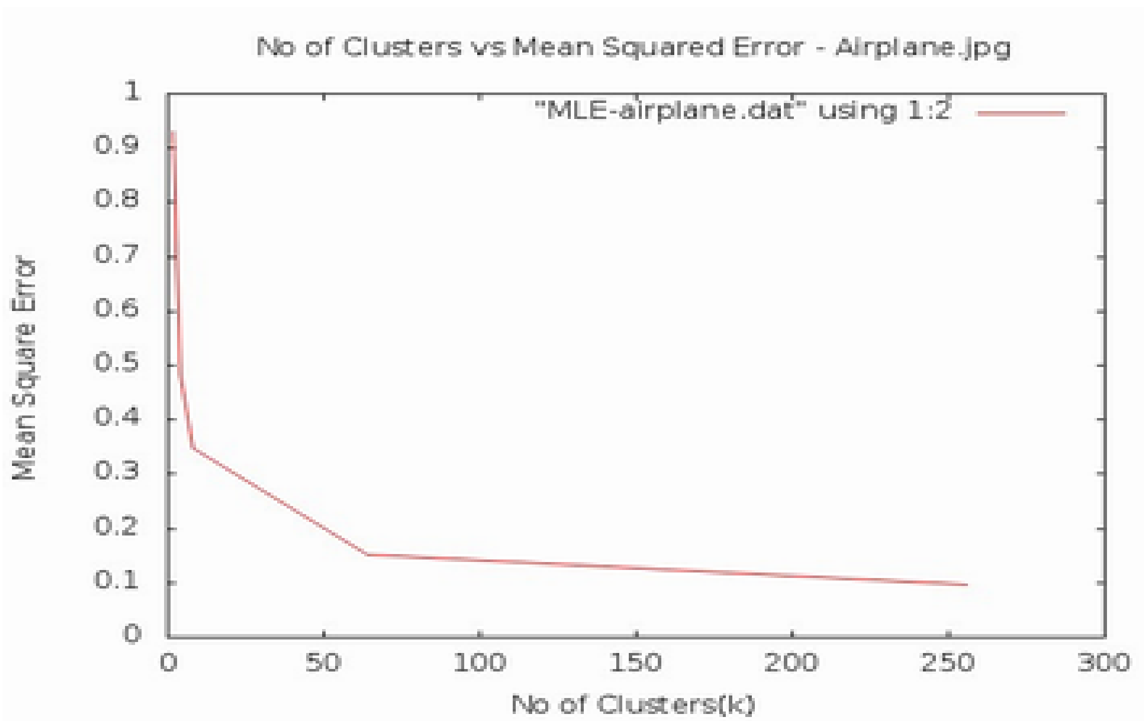
Building.jpg

#k	#MSE
2	0.98080069098906
4	0.70243993001608
8	0.57067326425807
64	0.30411780260887
256	0.22314860217988



Airplane.jpg

#k	#MSE
2	0.93080299069565
4	0.48208807927778
8	0.34794332948337
64	0.15279342499476
256	0.097559916382746



Q2.2: Dagobert reconstructed the “compressed' test image obtained with K = 256 by replacing each tile by its closest prototype. For your convenience, Dagobert wrote a function tile.tileim() to transform tiles back to an image, to make it easier for you to repeat his results.

Solution: Compressed images for K = 256 for all the test images can be found in the same directory as this report :

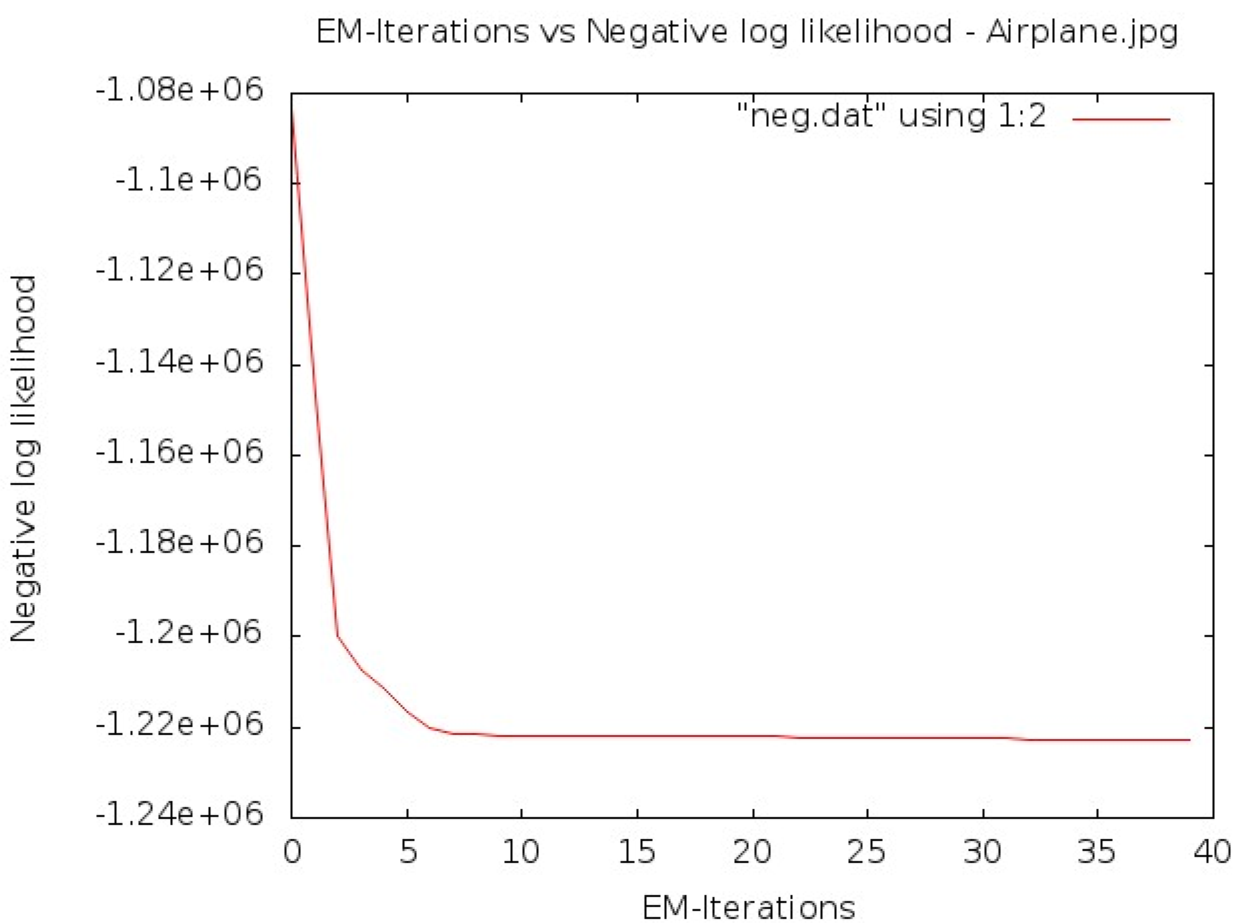
See bird-256.jpg; boat-256.jpg; airplane-256.jpg ; buildings-256.jpg

Q2.3: Compare with Dagobert the initial value of negative log-likelihood (after running k-means and one M step to compute the covariance matrices, using the binary responsibilities produced by K-means), and the value at the end of the convergence of EM.

Solution : It was observed the initial negative log likelihood is higher as compared to the one obtained at the end of convergence of EM. Therefore, EM algorithm does manage to minimize the log likelihood of the data which was the objective function.

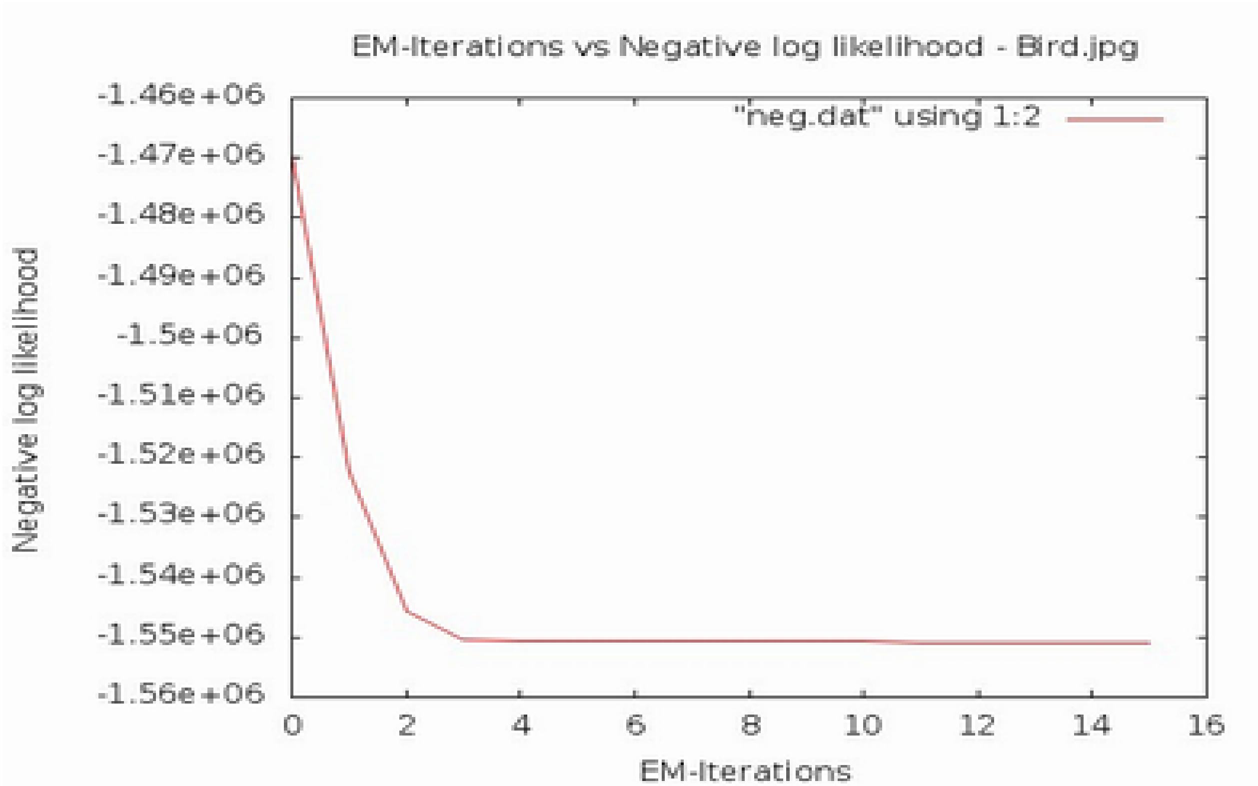
Airplane.jpg

Initial Value : -1082880.69627 Value at the end of convergence : -1222629.3456



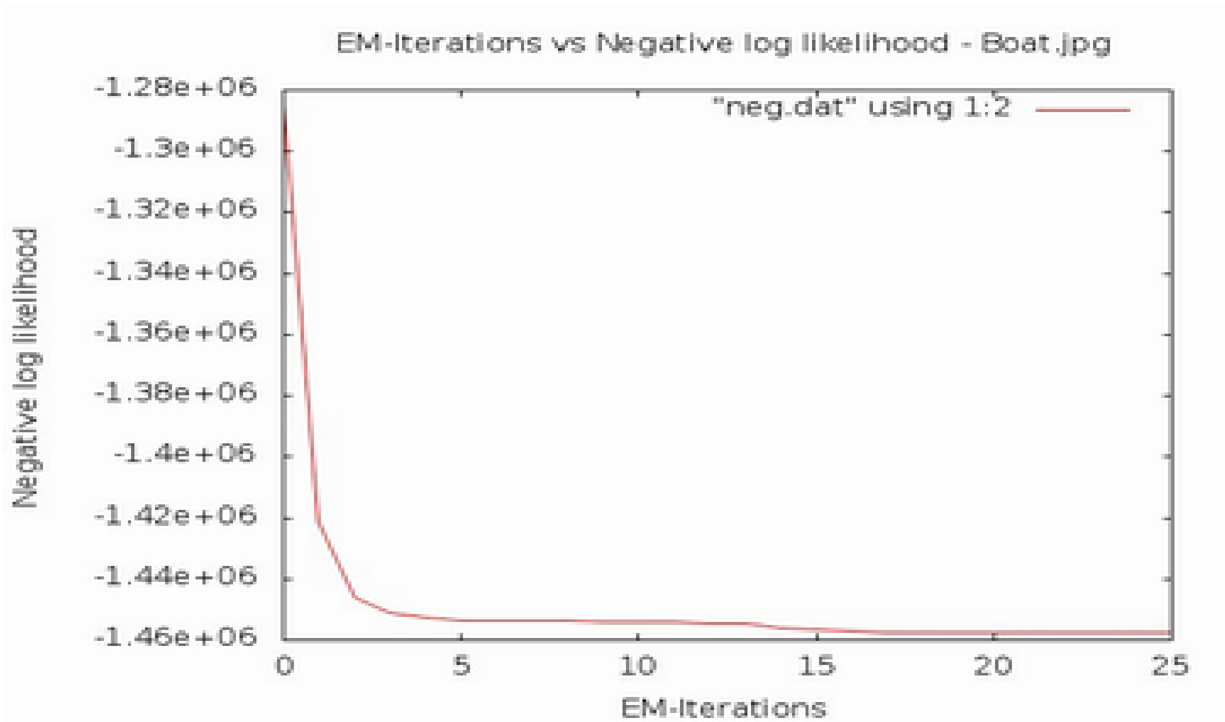
Bird.jpg

Initial Value : -1469387.5439781 Value at the end of convergence : -1550900.7967



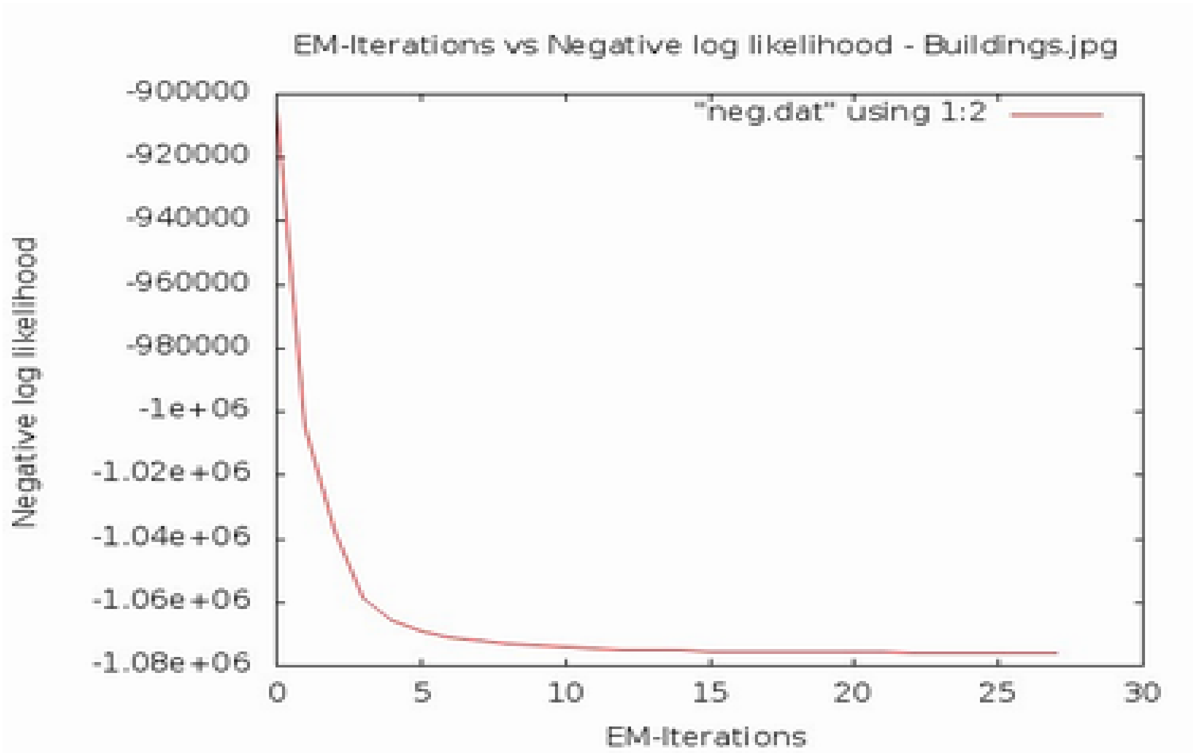
Boat.jpg

Initial Value : -1285081.274914 Value at the end of convergence : -1457543.009113



Building.jpg

Initial Value : -904262.49521055-   Value at the end of convergence : -1075825.4480113



Q3.1:

Solution : Following are the Histogram Entropies and Number of Bits for each different image.

Image	Histogram Entropy	Number of bits(approx)
Boat	**2.3881174685104**	**17910**
Airplane	**2.6003888815484**	**19503**
Buildings	**2.5519445295581**	**19140**
Bird	**2.71432763402**	**20357**

Q3.2: (Open question) - Dagobert has read a paper saying the histogram Hk we proposed above could actually be used as a feature for images regardless of the sizes of them. Can you propose a type of classification task where this idea may be good, so that Dagobert could give it a try?

Solution :

- Dagobert can use the Histogram Hk to do object recognition of images.
- Object recognition task can be seen as a special case of image classification which either can be binary classification(i.e whether an image is present or not) or multiclass classification (i.e which category is represented in the image)
- The histogram feature scheme simply collects the number of tiles for every cluster and uses them as the features to represent the images. For e.g Assuming no of clusters as constant, after processing two similar images(images with same object) using K-means clustering , the histogram distribution of both of them will be similar because the histogram distribution does not capture the correlation between different pixels
- Recent studies have shown that color is a dominating component in determining human being's perception of an image. Further, texture of an image can also be part of feature vector. Both the improvements can compensate for what is missing in black and white histogram distributions and can improve the ability of systems to predict the classification category of an image.