

<u>Unit 4 Unsupervised Learning (2</u>

Project 4: Collaborative Filtering via

Course > weeks)

> Gaussian Mixtures

> 5. Bayesian Information Criterion

5. Bayesian Information Criterion

Extension Note: Project 4 due date has been extended by 1 more day to August 22 23:59UTC.

So far we have simply set the number of mixture components K but this is also a parameter that we must estimate from data. How does the log-likelihood of the data vary as a function of K assuming we avoid locally optimal solutions?

To compensate, we need a selection criterion that penalizes the number of parameters used in the model. The Bayesian information criterion (BIC) is a criterion for model selection. It captures the tradeoff between the log-likelihood of the data, and the number of parameters that the model uses. The BIC of a model M is defined as:

$$\mathrm{BIC}\left(M\right) = l - \frac{1}{2}p\log n$$

where l is the log-likelihood of the data under the current model (highest log-likelihood we can achieve by adjusting the parameters in the model), p is the number of adjustable parameters, and n is the number of data points. This score rewards a larger log-likelihood, but penalizes the number of parameters used to train the model. In a situation where we wish to select models, we want a model with the highest BIC.

Implementing the Bayesian Information Criterion

1.0/1.0 point (graded)

Fill in the missing Bayesian Information Criterion (BIC) calculation (bic function) in common.py.

Available Functions: You have access to the NumPy python library as <code>np</code>, to the <code>GaussianMixture</code> class and to typing annotation <code>typing.Tuple</code> as <code>Tuple</code>.

```
20
          X: (n, d) array holding the data
21
          mixture: a mixture of spherical gaussian
22
          log_likelihood: the log-likelihood of the data
23
24
      Returns:
25
          float: the BIC for this mixture
26
27
      n, d = X.shape
28
      mu, var, p = mixture
29
      n_para = mu.shape[0] * mu.shape[1] + var.shape[0] + p.shape[0] - 1
      BIC = log_likelihood - 1/2 * n_para * np.log(n)
30
31
      return BIC
32
33
34
```

Press ESC then TAB or click outside of the code editor to exit

Correct

Test results

CORRECT

See full output

See full output

Solution:

The Bayesian Information Criterion for a mixture of spherical Gaussians is:

$$BIC\left(D; heta
ight) = l\left(D; heta
ight) - rac{k\left(d+2
ight) - 1}{2}\mathrm{log}\left(n
ight)$$

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You have used 4 of 20 attempts

• Answers are displayed within the problem

Picking the best K

1.0/1.0 point (graded)

Find the best K from [1,2,3,4] on the toy dataset. This will be the K that produces the optimal BIC score. Report the best K and the corresponding BIC score. Measure the BIC on EM models, only. Does the criterion select the correct number of clusters for the toy data?

Grader note: While the best BIC should be a negative value, due to earlier grader error, we have corrected the grader to accept both the positive and the negative value.

Solution:

Code:

```
def run_with_bic():
   max_bic = None
   for K in range(1, 5):
       max_11 = None
       best_seed = None
       for seed in range(0, 5):
            mixture, post = common.init(X, K, seed)
            mixture, post, 11 = naive_em.run(X, mixture, post)
           if max_ll is None or ll > max_ll:
                max_11 = 11
               best_seed = seed
       mixture, post = common.init(X, K, best_seed)
       mixture, post, 11 = naive_em.run(X, mixture, post)
       bic = common.bic(X, mixture, 11)
       if max_bic is None or bic > max_bic:
            max_bic = bic
       title = "EM for K=, seed=, 11=, bic=".format(K, best_seed, 11, bic)
       print(title)
       common.plot(X, mixture, post, title)
```

 K
 BIC

 1
 -1315.5056

 2
 -1195.0397

 3
 -1169.2589

 4
 -1180.0121

From the BIC values above, the best K is 3, which seems to fit the toy data.

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You have used 1 of 10 attempts

• Answers are displayed within the problem

Discussion

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