CSC411 Assignment 2

Yue Guo

November 9, 2017

1 Gaussian

1.1 P(y)

$P(\boldsymbol{x}|\ mu, \sigma) = \sum_{k=1}^{K} P(\boldsymbol{x}|y=k,\ mu, \sigma) P(y=k|\mu, \sigma)$
$= \sum_{k=1}^{K} \alpha_k P(\boldsymbol{x}|y=k,\ mu, \sigma)$
$= \sum_{k=1}^{K} \alpha_k (\prod_{i=1}^{D} 2\pi\sigma_i)^{\frac{1}{2}} exp\{-\sum_{i=1}^{D} \frac{1}{2\sigma_i^2}(x_i - \mu_{ki})^2\}$

1.2 visualization

$P(y|\boldsymbol{x},\ mu, \sigma) = \frac{P(\boldsymbol{x}, y=k|\mu,\sigma)}{P(\boldsymbol{x}|\mu,\sigma)}$
$= \frac{P(\boldsymbol{x}|y=k,\ mu,\sigma)P(y=k|\mu,\sigma)}{P(\boldsymbol{x}|\mu,\sigma)}$
$= \frac{\alpha_k (\prod_{i=1}^{D} 2\pi\sigma_i^2)^{-\frac{1}{2}} exp\{-\sum_{i=1}^{D} \frac{1}{2\sigma_i^2}(x_i - \mu_{ki})^2\}}{\sum_{k=1}^{K} \alpha_k (\prod_{i=1}^{D} 2\pi\sigma_i^2)^{-\frac{1}{2}} exp\{-\sum_{i=1}^{D} \frac{1}{2\sigma_i^2}(x_i - \mu_{ki})^2\}}$

1.3 visualization

$-logP(y^{(1)}, x^{(1)}, ..., y^{(N)}, x^{(N)}|\theta)$
$= -logP(y^{(1)}, x^{(1)}|\theta) - logP(y^{(2)}, x^{(2)}|\theta) ... - log(y^{(N)}, x^{(N)}|\theta)$
$= \sum_{k=1}^{K} -log[\alpha_k(\prod_{i=1} D2\pi\sigma_i^2)^{-\frac{1}{2}} exp\{-\sum_{i=1}^{D} \frac{1}{2\sigma_i^2}(x_i - \mu_{ki})^2\}]$
$= \sum_{k=1}^{K} \sum_{i=1}^{D} \frac{1}{2\sigma_i^2}(x_i - \mu_{ki})^2 + \sum_{k=1}^{K} -log[\alpha_k(\prod_{i=1}^{D} 2\pi\sigma_i^2)^{-\frac{1}{2}}$
$= \sum_{k=1}^{K} \sum_{i=1}^{D} \frac{1}{2\sigma_i^2}(x_i - \mu_{ki})^2 + \sum_{k=1}^{K} \frac{1}{2} log[\alpha_k(\prod_{i=1}^{D} 2\pi\sigma_i^2)$
$= \sum_{k=1}^{K} \sum_{i=1}^{D} \frac{1}{2\sigma_i^2}(x_i - \mu_{ki})^2 + \sum_{k=1}^{K} \sum_{i=1}^{D} [\frac{1}{2}\alpha_k \log(2\pi\sigma_i^2)]$

1.4 visualization

$\frac{\partial}{\partial \mu_{ki}} = \sum_{i=1}^{D} \frac{1}{2\sigma_i^2} 2(-x_i + \mu_{ki})\mathbb{1}(i=k)$
$= \sum_{i=1}^{D} \frac{1}{\sigma_i^2}(-x_i + \mu_{ki})\mathbb{1}(i=k)$
Setting $\frac{\partial}{\partial \mu_{ki}} = 0$, we have

$\sum_{i=1}^{D} \frac{1}{\sigma_i^2}(-x_i + \mu_{ki})\mathbb{1}(i=k) = 0$
$x_i = \frac{\sum_{i=1}^{D} \mu_{ki}\mathbb{1}(i=k)}{\sum_{i=1}^{D} \mathbb{1}(i=k)}$

1.5 visualization

$\frac{\partial}{\partial \sigma_i^2} = \sum_{k=1}^{K} \sum_{i=1}^{D} -\frac{1}{2}(x_i - \mu_{ki})^2 \frac{1}{\sigma_i^4} + \frac{1}{2} \sum_{k=1}^{K} \sum_{i=1}^{D} \frac{2\pi}{2\pi\sigma_i^2}$
$= \sum_{k=1}^{K} \sum_{i=1}^{D} -\frac{1}{2}(x_i - \mu_{ki})^2 \frac{1}{\sigma_i^4} + \frac{1}{2} \sum_{k=1}^{K} \sum_{i=1}^{D} \frac{1}{\sigma_i^2}$
$= \sum_{i=1}^{D} \frac{1}{2}[-(x_i - \mu_{ki})^2 \frac{1}{\sigma_i^4} + \frac{1}{\sigma_i^2}]\mathbb{1}(i=k)$

Setting $\frac{\partial}{\partial \sigma_i^2}$ to zero, we have
$\sum_{i=1}^{D} \mathbb{1}(i=k)(x_i - \mu_{ki})^2 \frac{1}{\sigma_i^4} = \sum_{i=1}^{D} \mathbb{1}(i=k) \frac{1}{\sigma_i^2}$
$\sum_{i=1}^{D} \mathbb{1}(i=k)(x_i - \mu_{ki})^2 = \sum_{i=1}^{D} \mathbb{1}(i=k) \sigma_i^2$
$\sigma_i^2 = \frac{\sum_{i=1}^{D} \mathbb{1}(i=k)(x_i - \mu_{ki})^2}{\sum_{i=1}^{D} \mathbb{1}(i=k)}$

2 Handwritten digits

2.1 KNN

1. Plot of digit means

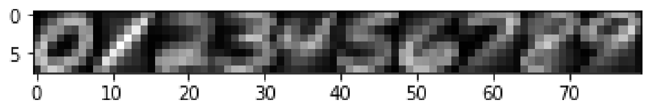

Figure 1:

2.1.1 KNN Euclidean

(a) K = 1, test accuracy = 0.96875, train accuracy = 1.0

(b) K = 15, test accuract = 0.9585 , train accuracy = 0.959428571429

2.1.2 Break ties

In my program, I have the array label_count[0 , 10] in function def query_knn(self, test_point, k): that stores the number of neighbours with the digit label corresponding to the index of label_count array. I find the maximum number in label_count, and the index of the max is the majority vote. If there are multiple, the function label_count.argmax() will pick the index that comes first. This is justified in class, we can break ties randomly or assign to the first maximum vote.

2.1.3 K = 1 to 15

K	Training Accuracy	Average Fold	Test Accuracy
1	cell5	0.9644285714285715	0
2	cell8	0.9575714285714285	0

[0.9644285714285715, 0.9575714285714285, 0.9634285714285715, 0.961, 0.9608571428571429, 0.959, 0.957857142857143, 0.9574285714285715, 0.9555714285714286, 0.9528571428571428, 0.9522857142857143, 0.9514285714285714, 0.9504285714285714, 0.95]

2.2 Conditional Gaussian

2.2.1 Plot of log

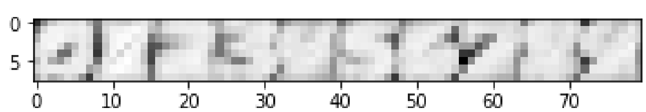

Figure 2:

2.3 Naives Bayes

2.3.1 Plot of η

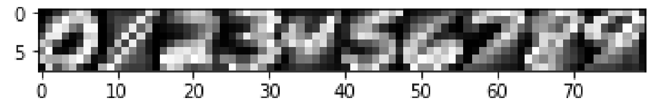

Figure 3:

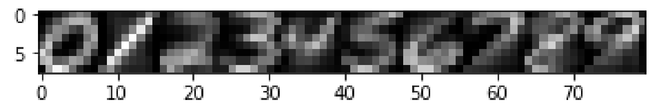

Figure 4: