This note explains essential stuff to understand a Naive Bayes classifier trained with both labeled data and unlabeled data [1, 2].

1 List of Important Terminologies

1. Q funtion of an EM algorithm is either of the following:

$$\sum_{d \in D} \sum_{c \in C} P(c|d;\theta) \log P(c,d;\theta)$$

$$\sum_{d \in D} E_{P(c|d;\theta)}[\log P(c,d;\theta)]$$

2. The objective function of a Naive Bayes classifier when conducting a maximum a posteriori estimation

$$\log P(\theta) + \log P(D)$$

3. Let $q_{w,c}$ be a probability that a word w is chosen given class c i.e.

$$q_{w,c} = P(W = w | C = c)$$

2 Naive Bayes

Naive Bayes models

C: a class of document e.g. positive/negative

D: a document

We want to know the class C of a document D by calcualting the following term:

$$C' = \arg\max_{C} P(C|D)$$

The model tries to calculate

$$P(C|D) \propto P(C)P(D|C)$$

So now, we want to know $P(C)$ and $P(D|C)$.

Assumes that a word w occur independently within a document given a class.

$$P(D|C) = \prod_{w \in D} P(w|C)$$

3 Notes

1. Since we want to handle probabilities, the constraint $\sum_c p_c = 1$ is set. Therefore, we want to optimize using the method of Lagrange multiplier.

2. Assume that the data likelihood when incorporating both labeled data and unlabeled data is [2]

$$\log P(D^l)P(D^u) = \log P(D^l) + \log P(D^u)$$

As a result, the objective function of a Naive Bayes classifier becomes

$$
\begin{aligned}
\underset{\theta}{\text{maximize}} \quad & \log P(\theta) + \log P(D^l) + \log P(D^u) \\
\text{subject to} \quad & \sum_{c \in C} p_c = 1 \\
& \sum_{w} q_{w,c} = \sum_{w} P(W = w | C = c) = 1
\end{aligned}
$$

References

[1] Kamal Nigam, Andrew Kachites McCallum, Sebastian Thrun, and Tom Mitchell. Text classification from labeled and unlabeled documents using em. *Machine learning*, 39(2-3):103–134, 2000.

[2] 高村 大也. **言語処理のための機械学習入門 (自然言語処理シリーズ)**. コロナ社, 7 2010.