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CS 464 Introduction to Machine Learning

HW 1

Q1) 1.1) $P(F_P) = ?$

Given $\longrightarrow$ $P(F_P \mid P) = 0.95$ $\quad P(P) = 0.45$

$P(F_P \mid M) = 0.6$ $\quad P(M) = 0.30$

$P(F_P \mid U) = 0.1$ $\quad P(U) = 0.25$

$$P(F_P) = P(F_P \mid P) \cdot P(P) + P(F_P \mid M)P(M) + P(F_P \mid U)\,P(U)$$

$$= 0.95 \times 0.45 + 0.6 \times 0.3 + 0.1 \times 0.25$$

$$= 0.4275 + 0.18 + 0.025 = 0.6325$$

$$\boxed{P(F_P) = 0.6325}$$

1.2) $P(P \mid F_P) = ?$

By Bayes Rule;

$$P(P \mid F_P) = \frac{P(F_P \mid P)\,P(P)}{P(F_P)} = \frac{0.95 \times 0.45}{0.6325} = 0.6761$$

$$\boxed{P(P \mid F_P) = 0.6761}$$

1.3) $P(P \mid F_N) = ?$

$P(F_N \mid P) = 1 - P(F_P \mid P) = 0.05$

$P(F_N \mid M) = 1 - P(F_P \mid M) = 0.4$

$P(F_N \mid U) = 1 - P(F_P \mid U) = 0.9$

$$P(F_N) = P(F_N \mid P)\,P(P) + P(F_N \mid M)\,P(M) + P(F_N \mid U)\,P(U) = 0.05 \times 0.45 + 0.4 \times 0.3 + 0.9 \times 0.2$$

$$P(F_N) = 0.0225 + 0.12 + 0.225 = 0.3675$$

By Bayes;

$$P(P \mid F_N) = \frac{P(F_N \mid P)\,P(P)}{P(F_N)} = \frac{0.05 \times 0.45}{0.3675} = 0.0612$$

$$\boxed{P(P \mid F_N) = 0.0612}$$

2.1

1.

With the help of “q3.py”, I calculated the percentage of spam emails as 28.6%.

2.

Due to the training set having a greater proportion of non-spam emails (71.40%) than spam emails (28.60%), one of the groups is skewed more than the other. Unbalanced training data can have an impact on the algorithm. Based on the disparity, the classifier may be skewed regarding the dominant, which could result in more false negatives or false positives. To put it another way, the model might be good for the dominant class but bad for the minority class, which makes it less trustworthy in real-world situations.

3.

The stated accuracy may be deceptive if the dataset is biased regarding one of the groups. A classifier's high precision may only sometimes mean it is doing well in both groups. For example, the classifier would still achieve high accuracy in a collection with significant imbalance if it merely predicted almost every class for all examples. With this reason, in addition to accuracy, other performance measures like precision, recall, and F1 score should also be taken into account when assessing the model's performance. These measures give information about how well the classifier performs for specific classes, which can be used to spot possible class imbalance problems.

2.2

The output of the Multinomial Naive Bayes model is below;

Question 2.2

Accuracy: 0.9507

Confusion Matrix:

Predicted 0 1

Actual

0 684 34

1 17 300

Number of wrong predictions: 51

2.3

The output of the Bernoulli Naïve Bayes Model is below;

Accuracy with additive smoothing:0.9478

Confusion Matrix with additive smoothing:

Predicted 0 1

Actual

0   681   37

1   17 300

In conclusion, despite the high stated accuracy, the skewed composition of the dataset makes it risky to base decisions purely on accuracy. To more fully comprehend the model's success on both spam and non-spam emails, it is essential to take into account additional measures like precision, recall, and F1 score in addition to the confusion matrix.

2.4

The output of the Bernoulli Naïve Bayes Model is below;

Accuracy with Bernoulli Naive Bayes: 0.9159

Confusion Matrix with Bernoulli Naive Bayes:

Predicted   0   1

Actual

0   694   24

1   63 254

The test group precision in the Bernoulli Naive Bayes model is 0.9159. The Bernoulli Naive Bayes model possesses poorer total precision when compared to the Multinomial Naive Bayes model (accuracy 0.9507) and the Multinomial Naive Bayes with additive smoothing (accuracy 0.9478). The way the Bernoulli and Multinomial Naive Bayes models manage the existence of words in the texts is the primary distinction among them. The Multinomial Naive Bayes model takes into account the frequency of the words in the emails, whereas the Bernoulli Naive Bayes model solely takes into account the existence-1 or lack-0 of words in the emails. In addition, the Multinomial model treats the features as quantities of word occurrences, whereas the Bernoulli model considers the features as binary traits. According to the confusion matrices, the Multinomial Naive Bayes models have more false positives compared to false negatives.

In contrast, the Bernoulli Naive Bayes models have more false positives than false negatives. This suggests that the Bernoulli Naive Bayes model is more cautious when forecasting spam emails, which may be advantageous when reducing the wrong classification of legitimate emails as spam. The algorithm is less successful at identifying genuine spam emails due to the higher false positives that result from that. In conclusion, the Bernoulli Naive Bayes model is distinct from the Multinomial Naive Bayes model in that it treats traits as binary rather than matters, leading to lower overall precision and a more cautious method of identifying spam emails. According to the unique use case and objectives, either model may be better suited for a particular application.

2.5

Bernoulli Naive Bayes, Multinomial Naive Bayes, and Multinomial Naive Bayes with Additive Smoothing algorithms produced similar findings. Still, the MNB and MNB-AS models were more accurate (0.9507 and 0.9478, respectively) than the BNB model. (0.9159). But other metrics be taken in addition to accuracy. According to the confusion matrices, the BNB model has lower false positives than the MNB and MNB-AS models, making it less likely to label legitimate emails as spam mistakenly.

However, compared to the MNB and MNB-AS models, the BNB model has more tremendous false positives, suggesting that it is less successful at identifying genuine spam emails. The selection of an algorithm for a real-world application relies on particular objectives and criteria. The BNB approach may be more appropriate if eliminating false positives is more crucial.

Nevertheless, the MNB or MNB-AS models would be superior options if identifying more spam emails was the main objective because they have higher total precision and fewer false positives. Accuracy may need to be more accurate as a success measure for this algorithm because it fails to account for the trade-offs across false positives and false negatives. Other indicators that give a complete picture of the classifier's success are precision, recall, and F1 score. Focusing exclusively on accuracy could result in poor choices in situations with unbalanced datasets or as various kinds of wrong classifications have distinct costs.