HW1 CS464-1
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1 Probability Review

Q1.1

$P(B)$ =The event that a blue coin is chosen
$P(R)$ = The event that the red coin is chosen
$P(Y)$ = The event that the yellow coin is chosen
$P(BOX1)$ =The probability that box 1 is chosen
$P(BOX2)$ = Event that box 2 is chosen

$P(B) = P(B|BOX1) * P(BOX1) + P(B|BOX2) * P(BOX2) = 2/3 * 1/2 + 1/3 * 1/4 = 7/12$

$P(Y) = P(Y|BOX1) * P(BOX1) = 1/3 * 1/2 = 1/6$

$P(R) = P(R|BOX2) * P(BOX2) = 1/2 * 1/2 = 1/4$

What we want
$P(A) =$ Event that tail comes twice

$P(T|B) = 1/2$ The event that blue coin landed tail.

$P(T|Y) = 3/4$ The event that yellow coin landed tail.

$P(T|R) = 9/10$ The event that red coin landed tail.

$$\begin{aligned} P(A) &= P(A|B) * P(B) + P(A|Y) * P(Y) + P(A|R) * P(R) \\ &= [P(T|B)]\text{^}2 * P(B) + [P(T|Y)]\text{^}2 * P(Y) + [P(T|R)]\text{^}2 * P(R) \\ &= 1/4 * 7/12 + 9/16 * 1/6 + 81/100 * 1/4 = 7/48 + 9/96 + 81/400 \\ &= 0.44208 \end{aligned}$$

Q1.2

Blue coins are fair, so let's only check blue coins.

$P(B|A) = (P(A|B) * P(B))/P(A) = (1/2 * 1/2 * 7/12)/(7/48 + 9/96 + 81/400) = 0.32988$

Q1.3

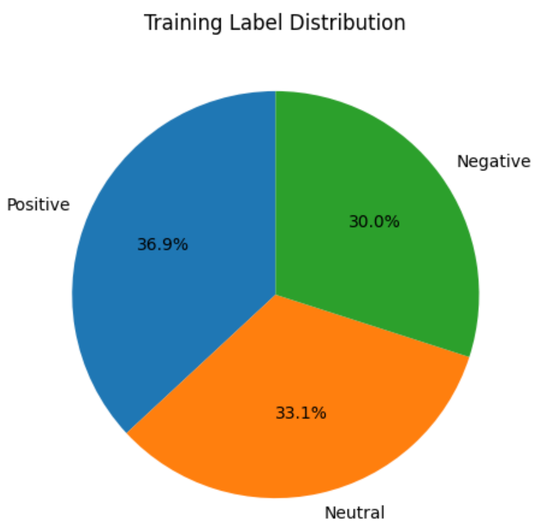
We check red this time.

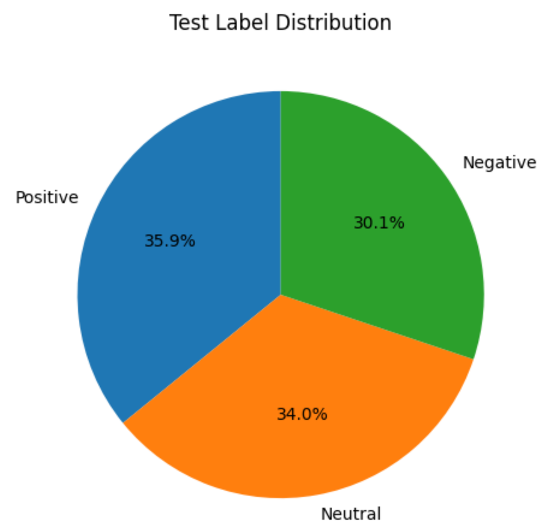
$P(R|A) = (P(A|R) * P(R))/P(A) = (81/100 * 1/4)/(7/48 + 9/96 + 81/400) = 0.45806$

2 Amazon Reviews Classification

Question 3.1

1. What are the percentages of each category in the y_train.csv y_test.csv? Draw a pie chart showing percentages.





Y can take 0,1,2, which are negative, neutral, and positive, respectively.

	Training (out of 1)	Test (out of 1)
0	689/2300 = 0.2995652	211/700 = 30.14286
1	762/2300 = 0.3312043	238/700 = 34.00000
2	849/2300 = 0.3691304	251/700 = 35.85714

2. What is the prior probability of each class? Write your answer to the report.

	Training (out of 1)
0	(689+211) / 2300 = 0.3
1	(762+238) / 2300 = 0.333
2	(849+251) / 2300 = 0.367

3. Is the training set balanced or skewed towards one of the classes? Do you think having an imbalanced training set affects your model? If yes, please explain briefly how it can affect the model.

The overall dataset, comprising both training and validation data, shows a class distribution that closely aligns with that of the training set. This similarity indicates that no class is notably underrepresented. However, a class imbalance can still lead the model to favor the majority class in predictions, potentially reducing accuracy for minority classes.

Maintaining a balanced dataset is essential to minimize skew and enhance model performance. As discussed in class, if the model is not trained sufficiently, it may be too simplistic or underfitting to capture the underlying feature patterns, resulting in lower prediction accuracy.

4. How many times do the words ”good” and ”bad” appear in the training documents with the label ”positive”, including multiple occurrences, and what are the log ratio of their occurrences within those documents, i.e, ln(P(good|Y = positive)) and ln(P(bad|Y = positive))?

The count of "good" occurrences when the output label is 2 (indicating a positive review) is 207. In contrast, the count of "bad" occurrences for the same output label is 12.

$$ln(207/849)/ln(12/849) = 0.33137$$

Question 3.2 Confusion Matrix for Multinomial Naïve Bayes (α=0)

	Predicted			
Actual	0.301	Negative	Neutral	Positive
	Negative	211	0	0
	Neutral	238	0	0
	Positive	251	0	0

Question 3.3 Confusion Matrix for Multinomial Naïve Bayes (α=1)

	Predicted			
Actual	0.649	Negative	Neutral	Positive
	Negative	151	45	15
	Neutral	73	86	79
	Positive	13	21	217

Using additive smoothing with a Dirichlet prior (α=1) prevents zero probabilities for words that are absent in the texts. This approach enhances test set accuracy and generalization, particularly when training data is limited. My findings support this improvement, as evidenced by the higher accuracy in Table 2 compared to Table 1.

Question 3.4 Confusion Matrix for Bernoulli Naïve Bayes

	Predicted			
Actual	0.641	Negative	Neutral	Positive
	Negative	113	90	8
	Neutral	29	180	29
	Positive	19	76	156

The slightly higher accuracy of the Bernoulli Naive Bayes model suggests that representing information based on the presence or absence of words is more effective than relying on word frequencies. This distinction is important because, as highlighted by the Bernoulli model, performance improves in cases where the mere presence of specific words holds more significance. In contrast, the Multinomial model considers both word presence and frequency, meaning that word frequency plays a significant role in determining class labels.