Applied Machine Learning - Homework 2

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Programming Exercise

1) Binary Classification on Text Data

Question 1a)

In this project, I will be participating in the NLP with Disaster Tweets Kaggle competition, where the task is to predict whether or not a tweet is about a real disaster. I plan to implement several machine learning techniques to classify this text data and ultimately identify the most effective NLP approach.

You can find the dataset here: https://www.kaggle.com/c/nlp-getting-started

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn

train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
```

There are 7613 and 3263 data points in the train and test datasets, respectively. In the train dataset, 43.0% of the tweets are of real disasters and the remaining 57.0% are fake.

In [5]:
```
print("Train Data: {} rows and {} columns".format(train.shape[0], train.shape[1]))
print("Test Data: {} rows and {} columns".format(test.shape[0], test.shape[1]))


target_counts = train.groupby('target')['target'].count()
# Create a DataFrame with counts and percentages
target_summary = pd.DataFrame({
    'count': target_counts,
    'percentage': (target_counts / train['target'].count())*100
})

target_summary
```

```
Train Data: 7613 rows and 5 columns
Test Data: 3263 rows and 4 columns
```

Out[5]:

target	count	percentage
0	4342	57.034021
1	3271	42.965979

Question 1b)

Splitting Training Data: 70% for Training Set, 30% for Development Set

Since we do not know the correct values of labels in the test data, we will split the training data from Kaggle into a training set and a development set (a development set is a held out subset of the labeled data that we set aside in order to fine-tune models, before evaluating the best model(s) on the test data). The idea is that we will train different models on the training set, and compare their performance on the development set, in order to decide what to submit to Kaggle.

In [6]:
```
from sklearn.model_selection import train_test_split

train_set, dev_set = train_test_split(train, test_size=0.3, random_state=42)
```

In [7]:
```
dev_set.shape
```

Out[7]: (2284, 5)

Question 1c)

Preprocessing Data

1) Converting all words to lowercase

Converting words to lowercase helps with dimensionality reduction. Words like "Heat" and "het" are considered different by most algorithms if case sensitivity is preserved, so lowercasing makes sure that such variations are treated uniformly. This helps models focus on the meaning of words rather than their formatting, improving consistency and accuracy in this classification task.

In [8]:
```
train_set2 = train_set.copy()
train_set2.text = train_set2.text.str.lower()
train_set2.head()
```

Out[8]:

	id	keyword	location	text	target
1186	1707	bridge%20collapse	NaN	ashes 2015: australia□ûªs collapse at trent br...	0
4071	5789	hail	Carol Stream, Illinois	great michigan technique camp\nb1g thanks to @...	1
5461	7789	police	Houston	cnn: tennessee movie theater shooting suspect ...	1
5787	8257	rioting	NaN	still rioting in a couple of hours left until ...	1
7445	10656	wounds	Lake Highlands	crack in the path where i wiped out this morni...	0

2) Eliminating punctuation

Much like converting words to lowercase, removing punctuation in NLP helps with dimensionality reduction. Punctuation marks often don't carry significant semantic meaning in many tasks, particularly when the focus is on classification. Hence, eliminating punctuation helps to make the feature space less noisy, which can improve the model's generalizability. This in-turn allows the model to concentrate on the text's content rather than on formatting elements that add little to the underlying meaning.

I chose to eliminate punctuation before lemmatization, because punctuation can interfere with accurately identifying word roots and forms.

In [9]:
```
train_set2['text'] = train_set2['text'].str.replace(r'[^\x00-\x7F]+|[^\w\s]', '', regex=True)
train_set2['keyword'] = train_set2['keyword'].str.replace(r'[^\x00-\x7F]+|[^\w\s]', '', regex=True)
train_set2.head()
```

Out[9]:

	id	keyword	location	text	target
1186	1707	bridge20collapse	NaN	ashes 2015 australias collapse at trent bridge...	0
4071	5789	hail	Carol Stream, Illinois	great michigan technique camp\nb1g thanks to b...	1
5461	7789	police	Houston	cnn tennessee movie theater shooting suspect k...	1
5787	8257	rioting	NaN	still rioting in a couple of hours left until ...	1
7445	10656	wounds	Lake Highlands	crack in the path where i wiped out this morni...	0

3) Lemmatization

Lemmatization aids in NLP tasks by grouping morphologically related words together (i.e. reducing words to their root form) and treating them similarly. This normalization process reduces the vocabulary size, helping with dimensionality reduction. Moreover, focusing the model on core meanings rather than variations in word forms improves accuracy, precision, and efficiency of our model.

Another notable preprocessing step in NLP is stemming. The practical distinction between stemming and lemmatization is that, where stemming merely removes common suffixes from the end of word tokens, lemmatization ensures the output word is an existing normalized form of the word (for example, lemma) that can be found in the dictionary. (Link: https://www.ibm.com/topics/stemming-lemmatization)

A note on lemmatization: Part of speech (POS) tagging is a crucial step in lemmatization. POS essentially assigns each word tag signifying its syntactic function in the sentence.

In [10]:

```
#!pip install nltk
import nltk### Converting all words to lowercaseMuch like converting words to lowercase, eliminating punctuations he
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet

#nltk.download('wordnet');
#nltk.download('omw-1.4');
#nltk.download('averaged_perceptron_tagger');
#nltk.download('punkt');
```

In [11]:

```
import pandas as pd
import nltk
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet
from nltk import pos_tag

lemmatizer = WordNetLemmatizer()

# Function to get WordNet POS tag
def get_wordnet_pos(tag):
    if tag.startswith('J'):
        return wordnet.ADJ
    elif tag.startswith('V'):
        return wordnet.VERB
    elif tag.startswith('N'):
        return wordnet.NOUN
    elif tag.startswith('R'):
        return wordnet.ADV
    else:
        return wordnet.NOUN


def lemmatize_text(text):
    words = nltk.word_tokenize(text)
    pos_tags = pos_tag(words)
    lemmatized_words = [lemmatizer.lemmatize(word, get_wordnet_pos(tag)) for word, tag in pos_tags]
    return ' '.join(lemmatized_words)


train_set2['text'] = train_set2['text'].apply(lemmatize_text)
train_set2.head()
```

Out[11]:

	id	keyword	location	text	target
1186	1707	bridge20collapse	NaN	ash 2015 australia collapse at trent bridge am...	0
4071	5789	hail	Carol Stream, Illinois	great michigan technique camp b1g thanks to bm...	1
5461	7789	police	Houston	cnn tennessee movie theater shoot suspect kill...	1
5787	8257	rioting	NaN	still riot in a couple of hour leave until i h...	1
7445	10656	wounds	Lake Highlands	crack in the path where i wipe out this momin...	0

4) Strip stop words

In natural language processing (NLP), stop words are filtered out to enhance text analysis and computational efficiency. Eliminating stop words can improve the accuracy and relevance of NLP tasks by drawing attention to the more important words or content words. Examples of stop words are "the", "and", "or" etc.

In [12]:

```
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
# nltk.download('stopwords')  # Uncomment this line if you haven't downloaded the stopwords
# nltk.download('punkt')       # Uncomment this line if you haven't downloaded the punkt tokenizer

stop_words = set(stopwords.words('english'))

def remove_stop_words(text):
    if isinstance(text, str):

        words = word_tokenize(text)

        return ' '.join([word for word in words if word.lower() not in stop_words])
    return text


train_set2['text'] = train_set2['text'].apply(remove_stop_words)
train_set2['keyword'] = train_set2['keyword'].apply(remove_stop_words)


train_set2.head()
```

Out[12]:

	id	keyword	location	text	target
1186	1707	bridge20collapse	NaN	ash 2015 australia collapse trent bridge among...	0
4071	5789	hail	Carol Stream, Illinois	great michigan technique camp b1g thanks bmurp...	1
5461	7789	police	Houston	cnn tennessee movie theater shoot suspect kill...	1
5787	8257	rioting	NaN	still riot couple hour leave class	1
7445	10656	wounds	Lake Highlands	crack path wipe morning beach run surface woun...	0

5) Strip @ and URLs

Since our text is tweets, I will add another step to remove @ and URLs to reduce dimensionality and improve computational efficiency.

In [13]:

```
import re
def remove_urls(text):
    url_pattern = r'http[s]?://\S+|www\.\S+|\bhtt(?:p|ps)?[^\s]+\b'
    return re.sub(url_pattern, '', text).strip()

train_set2['text'] = train_set2['text'].apply(remove_urls)
train_set2['text'] = train_set2['text'].str.replace(r'@', '', regex=True)
train_set2.head()
```

Out[13]:

	id	keyword	location	text	target
1186	1707	bridge20collapse	NaN	ash 2015 australia collapse trent bridge among...	0
4071	5789	hail	Carol Stream, Illinois	great michigan technique camp b1g thanks bmurp...	1
5461	7789	police	Houston	cnn tennessee movie theater shoot suspect kill...	1
5787	8257	rioting	NaN	still riot couple hour leave class	1
7445	10656	wounds	Lake Highlands	crack path wipe morning beach run surface woun...	0

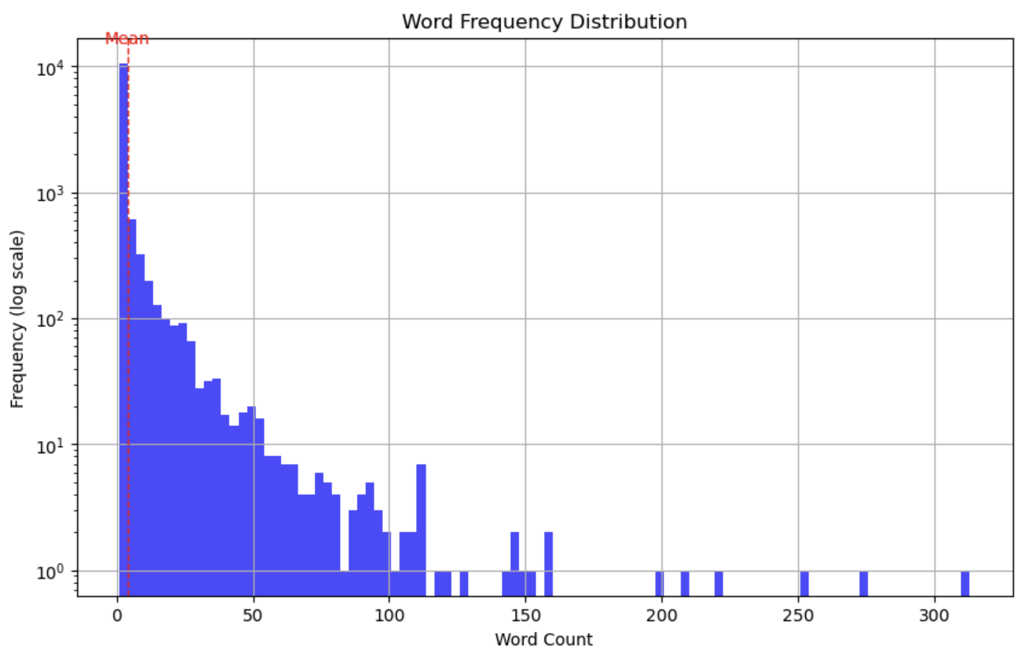
Question 1d)

Bag of Words Model

The next task is to extract features to represent each tweet using the binary "bag of words" model. The goal is to build a vocabulary from the words appearing in the dataset and to represent each tweet with a feature vector x whose length matches the size of the vocabulary. In this representation, x_i=1 if the ith vocabulary word appears in the tweet, and x_i=0 otherwise.

To accomplish this, I will use the CountVectorizer() class from Scikit-learn, setting the option binary=True to ensure that the feature vectors are binary. Additionally, I will specify the min_df parameter, which establishes a threshold to include only words that appear in at least k different tweets. This parameter is crucial for avoiding run-time and memory issues, as well as for eliminating noisy or unreliable features that could negatively impact learning.

I set min_df = 5 after analyzing the word frequency distribution in my train set. The histogram reveals a long tail, indicating that many words appear infrequently, with the mean frequency being 3.97. Most NLP projects recommend a min_df of 5, which helps focus on more common words while reducing noise by eliminating terms that rarely occur. Since the mean is ~4 and 5 is an appropriate choice, I think 5 is a good candidate for the min_df threshold.




```
Mean:  3.95
Median:  1.0
```

I took a look at the word and frequencies to ensure my preprocessing steps were successful. If there were any stop words or URLs in the dataframe below, I would know there was an error in preprocessing. This would also affect the choice of min_df (M).

In [13]:
```python
from sklearn.feature_extraction.text import CountVectorizer

M = 5  #based on mean and common NLP practices
vectorizer = CountVectorizer(binary=True, min_df=M)

X_train_set = vectorizer.fit_transform(train_set2['text'])
y_train_set = train_set2['target']

dev_set2 = preprocessing(dev_set)
X_dev_set = vectorizer.transform(dev_set2['text'])
y_dev_set = dev_set2['target']

num_features = len(vectorizer.get_feature_names_out())

print(f'Total number of features: {num_features}')

print(f'Training set shape: {X_train_set.shape}')
print(f'Development set shape: {X_dev_set.shape}')
print(f'First 10 words in the vocabulary: {word_freq_df.Word[:10].to_list()}')
```

```
Total number of features: 1842
Training set shape: (5329, 1842)
Development set shape: (2284, 1842)
First 10 words in the vocabulary: ['get', 'like', 'fire', 'im', 'amp', 'go', 'via', 'new', 'people', 'news']
```

Question 1e)
Part i)

Implementing Logistic Regression (Bag of Words Model)

Next, I trained a logistic regression models using bag of words feature vectors. I will use the F1/F score as the evaluation metric, the harmonic mean of precision and recall, as it gives a more comprehensive view of classifier performance than accuracy.

I implemented logistic regression without regularization terms (penalty=None). The F1 score for the training set (0.950) is close to 1, indicating that the model performs well in classifying positive instances and maintains a good balance between precision and recall. However, the F1 score for the development set is much lower (0.671) than that of the training set, suggesting that our model is **overfitting** on the training set and not performing as well on unseen data.

In [17]:
```
f1_scores = {}
```

In [18]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score

log_reg = LogisticRegression(penalty=None, solver='saga', max_iter=2000)  # No regularization
log_reg.fit(X_train_set, y_train_set)

y_train_pred = log_reg.predict(X_train_set)
y_dev_pred = log_reg.predict(X_dev_set)

# Calculate F1 scores
f1_train = f1_score(y_train_set, y_train_pred)
f1_dev = f1_score(y_dev_set, y_dev_pred)

# Print F1 Scores
print(f"F1 Score on Training Set using no regularization: {f1_train}")
print(f"F1 Score on Development Set using no regularization: {f1_dev}")

f1_scores['Logistic Regression - No Regularization '] = [f1_train, f1_dev]
```

```
F1 Score on Training Set using no regularization: 0.9500769738288981
F1 Score on Development Set using no regularization: 0.6789554531490015
```

Part ii) and iii)

In [19]:
```
log_reg_f1 = LogisticRegression(penalty='l1', solver='saga', max_iter=2000)  # No regularization
log_reg_f1.fit(X_train_set, y_train_set)

y_train_pred = log_reg_f1.predict(X_train_set)
y_dev_pred = log_reg_f1.predict(X_dev_set)

# Calculate F1 scores
f1_train = f1_score(y_train_set, y_train_pred)
f1_dev = f1_score(y_dev_set, y_dev_pred)

# Print F1 Scores
print(f"F1 Score on Training Set using L1 regularization: {f1_train}")
print(f"F1 Score on Development Set using L1 regularization: {f1_dev}")

f1_scores['Logistic Regression - L1 Regularization '] = [f1_train, f1_dev]

log_reg = LogisticRegression(penalty='l2', solver='saga', max_iter=2000)  # No regularization
log_reg.fit(X_train_set, y_train_set)

y_train_pred = log_reg.predict(X_train_set)
y_dev_pred = log_reg.predict(X_dev_set)

# Calculate F1 scores
f1_train = f1_score(y_train_set, y_train_pred)
f1_dev = f1_score(y_dev_set, y_dev_pred)

# Print F1 Scores
print(f"F1 Score on Training Set using L2 regularization: {f1_train}")
print(f"F1 Score on Development Set using L2 regularization: {f1_dev}")

f1_scores['Logistic Regression - L2 Regularization '] = [f1_train, f1_dev]
```

```
F1 Score on Training Set using L1 regularization: 0.8337193144974526
F1 Score on Development Set using L1 regularization: 0.7395143487858721
F1 Score on Training Set using L2 regularization: 0.8591160220994476
F1 Score on Development Set using L2 regularization: 0.7387289516567084
```

Question 1e part iv)

F1 Scores	Train	Development
Logistic Regression - No Regularization	0.950077	0.679651
Logistic Regression - L1 Regularization	0.833912	0.739514
Logistic Regression - L2 Regularization	0.859116	0.738729

I implemented logistic regression with L1 and L2 regularization.

1) The models with regularization are better at generalizability than the one with no regularization, as evidenced by the higher F1 score on the development set (~0.738 L1/L2 regularization vs 0.671 no regularization). Both L1 and L2 models have very similar F1 scores for development set, while L2 has a higher F1 score on the training set.

2) The models may still be overfitting, given the substantial difference between the training and development F1 scores.

Question 1e part v)

I examined the weight vector of the classifier with L1 regularization. Below are the 10 most important words for determining whether a tweet is about a real disaster. The sign of each coefficient indicates its correlation with the target variable (e.g. a negative coefficient suggests that the word's presence reduces the likelihood of the tweet being about a real disaster.) The absolute value of the coefficients reflects the strength of each word's influence on the target variable.

Predictably, words like 'hiroshima', 'earthquake', 'typhoon', 'wildfire', references to natural disasters, have high correlation with target variable. 'usagov' and 'mh370' are interesting words,

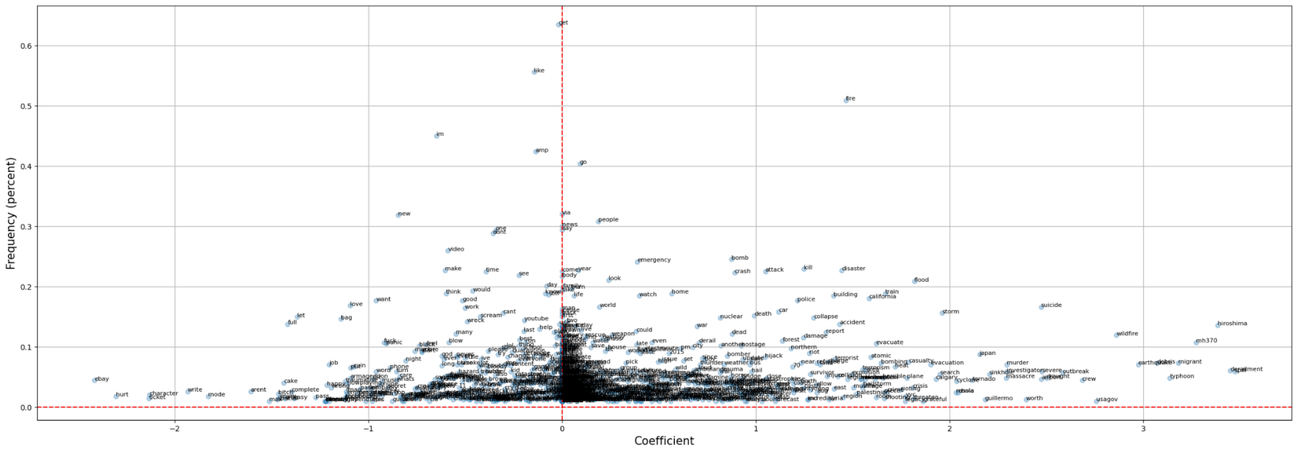
In [20]:
```
coefficients = log_reg_l1.coef_[0]
feature_names = vectorizer.get_feature_names_out()

importance_df = pd.DataFrame({'word': feature_names, 'coefficient': coefficients})
importance_df['abs_coefficient'] = importance_df['coefficient'].abs()
top_words = importance_df.sort_values(by='abs_coefficient', ascending=False)

top_words.head(10)
```

Out[20]:

	word	coefficient	abs_coefficient
1507	spill	3.472036	3.472036
458	derailment	3.447830	3.447830
780	hiroshima	3.383592	3.383592
1021	mh370	3.272992	3.272992
1027	migrant	3.179883	3.179883
1702	typhoon	3.137151	3.137151
442	debris	3.071063	3.071063
522	earthquake	2.973142	2.973142
1788	wildfire	2.860832	2.860832
1719	usagov	2.758280	2.758280



The majority of data points are clustered around the origin, forming an asymmetrical bell-shaped pattern. The words with coefficients at extreme values have lower frequency and may be less consistent/reliable.

Question 1f)

Implementing Bernoulli Naive Bayes (Bag of Words Model)

Next, I implemented a Bernoulli Naive Bayes classifier from scratch.

In [20]:
```
class BernoulliNaiveBayes:
    def __init__(self, alpha=1.0):
        self.alpha = alpha

    def fit(self, X, y):
        self.classes = np.unique(y)
        self.class_count = len(self.classes)
        self.feature_count = X.shape[1]

        self.word_counts = np.zeros((self.class_count, self.feature_count))
        self.class_counts = np.zeros(self.class_count)

        for idx, label in enumerate(y):
            self.class_counts[label] += 1
            self.word_counts[label] += X[idx]

        #Laplace
        self.probabilities = (self.word_counts + self.alpha) / (self.class_counts[:, None] + 2 * self.alpha)

    def predict(self, X):
        log_prob = np.log(self.probabilities)
        log_prob_complement = np.log(1 - self.probabilities)
        log_prior = np.log(self.class_counts / np.sum(self.class_counts))
        log_likelihood = X @ log_prob.T + (1 - X) @ log_prob_complement.T
        return np.argmax(log_likelihood + log_prior, axis=1)
```

In [21]:
```
X_train_binary = X_train_set.toarray()
y_train_binary = y_train_set.tolist()

X_dev_binary = X_dev_set.toarray()
y_dev_binary = y_dev_set.tolist()

nb_classifier = BernoulliNaiveBayes(alpha=1.0)
nb_classifier.fit(X_train_binary, y_train_binary)


y_train_pred = nb_classifier.predict(X_train_binary)
y_dev_pred = nb_classifier.predict(X_dev_binary)

f1_train = f1_score(y_train_binary, y_train_pred)
f1_dev = f1_score(y_dev_binary, y_dev_pred)


# Print F1 Scores
print(f"F1 Score on Training Set using Bernoulli Naive Bayes: {f1_train}")
print(f"F1 Score on Development Set using Bernoulli Naive Bayes: {f1_dev}")

f1_scores['Bernoulli Naive Bayes'] = [f1_train, f1_dev]
```

```
F1 Score on Training Set using Bernoulli Naive Bayes: 0.7925873129009264
F1 Score on Development Set using Bernoulli Naive Bayes: 0.7474402730375427
```

Question 1g)

F1 Scores	Train	Development
Logistic Regression - No Regularization	0.950077	0.679651
Logistic Regression - L1 Regularization	0.833912	0.739514
Logistic Regression - L2 Regularization	0.859116	0.738729
Bernoulli Naive Bayes	0.792587	0.747440

With an F1 score of 0.747, Bernoulli Naive Bayes, the generative model, performed the best on the development set.

Generative models (e.g., Naive Bayes) are computationally efficient, particularly with high-dimensional data like text. They are easy to implement/interpret and perform well even on small datasets.

However, the model's assumption on feature independence is often violated in text data, where words can be contextually dependent on each other.

Discriminative models (e.g., logistic regression) typically provide superior performance by effectively modeling complex decision boundaries and interactions between features.

However, these models do not capture the underlying data distribution, which can lead to overfitting if not properly regularized.

Model Assumptions

Bernoulli Naive Bayes: This model assumes that all features are conditionally independent given the class label. This is not necessarily true in NLP taasks, since words can be contextually dependent on each other.

Logistic Regression: This model does not assume independence among features, however, it does assumes a linear relationship between the target variable and the log odds of the dependent variable.

Using Bernoulli Naive Bayes for text classification is valid and efficient, particularly with binary or categorical data. However, its independence assumption may hinder performance compared to models like logistic regression, which don't have feature dependency assumptions. Interestingly, in the case above, Bernoulli outperformed logistic regression.

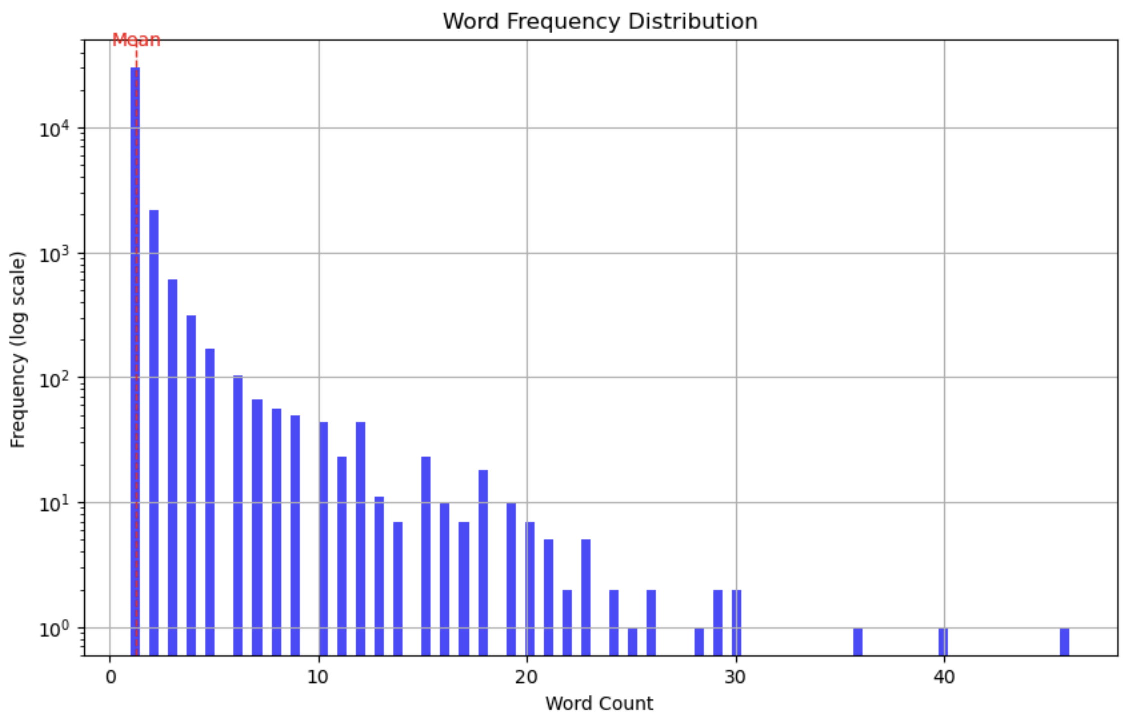
Question 1h)

N-Gram Model

The N-gram model is similar to the bag of words model, but instead of using individual words we use N-grams, which are contiguous sequences of words. For example, using N = 2, we would says that the text “Alice fell down the rabbit hole” consists of the sequence of 2-grams: ["Alice fell", "fell down", "down the", "the rabbit", "rabbit hole"], and the following sequence of 1-grams: ["Alice", "fell", "down", "the", "rabbit", "hole"]. All eleven of these symbols may be included in the vocabulary, and the feature vector x is defined according to xi = 1 if the i 'th vocabulary symbol occurs in the tweet, and xi = 0 otherwise.

To accomplish this, I will use the CountVectorizer() class from Scikit-learn and set ngram_range = (2,2). Additionally, I will investigate the best value for the min_df parameter.

I set min_df = 2 after investigating the word frequency distribution in my train set and runtime of M = 1 and 2. The histogram reveals a long tail, indicating that many words appear infrequently, with the mean frequency being 1.29. Min_df has to be an in integer, so I debated setting min_df = 1 or rounding up the mean to 2 and setting min_df equal to it. M = 2 has a slightly quicker run time and reasonable number of feature (3,647) compared to M = 1. Therefore, I think M = 2 is a good candidate for the M threshold.




```
Mean:  1.29
Median:  1.0
```

In [24]:
```python
import time

for i in [1, 2]:
    start_time = time.time()

    M = i
    vectorizer = CountVectorizer(ngram_range=(2,2), min_df=M)

    X_train_set = vectorizer.fit_transform(train_set2['text'])
    y_train_set = train_set2['target']

    dev_set2 = preprocessing(dev_set)
    X_dev_set = vectorizer.transform(dev_set2['text'])
    y_dev_set = dev_set2['target']

    num_features = len(vectorizer.get_feature_names_out())

    print(f'M = {i}')
    print(f'Total number of features: {num_features}')

    end_time = time.time()

    print("Execution time:", end_time - start_time, "seconds")
```

```
M = 1
Total number of features: 34120
Execution time: 1.3981082439422607 seconds
M = 2
Total number of features: 3647
Execution time: 1.3260278701782227 seconds
```

In [25]:
```
import time

M = 2
vectorizer = CountVectorizer(ngram_range=(2,2), min_df=M)

X_train_set = vectorizer.fit_transform(train_set2['text'])
y_train_set = train_set2['target']

dev_set2 = preprocessing(dev_set)
X_dev_set = vectorizer.transform(dev_set2['text'])
y_dev_set = dev_set2['target']

num_features = len(vectorizer.get_feature_names_out())

print(f'Total number of features: {num_features}')
print(f'Training set shape: {X_train_set.shape}')
print(f'Development set shape: {X_dev_set.shape}')
print(f'First 10 words in the vocabulary: \n {word_freq_df.Word[:10].to_list()}')
```

```
Total number of features: 3647
Training set shape: (5329, 3647)
Development set shape: (2284, 3647)
First 10 words in the vocabulary:
 ['body bag', 'suicide bomber', 'look like', 'northern california', 'youtube video', 'gon na', 'like youtube', 'cal
ifornia wildfire', 'oil spill', 'mass murder']
```

Implementing Logistic Regression (N-gram Model)

In [26]:
```
f1_scores_ngram = {}
```

In [27]:
```
for i in [None, 'l1', 'l2']:
    log_reg = LogisticRegression(penalty=i, solver='saga', max_iter=2000)
    log_reg.fit(X_train_set, y_train_set)

    y_train_pred = log_reg.predict(X_train_set)
    y_dev_pred = log_reg.predict(X_dev_set)

    # Calculate F1 scores
    f1_train = f1_score(y_train_set, y_train_pred)
    f1_dev = f1_score(y_dev_set, y_dev_pred)

    f1_scores_ngram[f'Logistic Regression - {i} Regularization '] = [f1_train, f1_dev]
```

Implementing Bernoulli Naive Bayes (N-gram Model)

In [28]:
```
X_train_binary = X_train_set.toarray()
y_train_binary = y_train_set.tolist()

X_dev_binary = X_dev_set.toarray()
y_dev_binary = y_dev_set.tolist()

nb_classifier = BernoulliNaiveBayes(alpha=1.0)
nb_classifier.fit(X_train_binary, y_train_binary)

y_train_pred = nb_classifier.predict(X_train_binary)
y_dev_pred = nb_classifier.predict(X_dev_binary)

f1_train = f1_score(y_train_binary, y_train_pred)
f1_dev = f1_score(y_dev_binary, y_dev_pred)

f1_scores_ngram['Bernoulli Naive Bayes'] = [f1_train, f1_dev]
```

Model Comparison

There is a stark difference in F1 scores of train and development set. This suggests that the N-gram model is overfitting on training set and failing to generalize on unseen data.

In [29]:
```
f1_scores_df = pd.DataFrame(f1_scores_ngram)
f1_scores_df.index = ['Train', 'Development']
f1_scores_df.index.name = 'F1 Scores - N-Gram Model'
f1_scores_df.T
```

Out[29]:

F1 Scores - N-Gram Model	Train	Development
Logistic Regression - None Regularization	0.789435	0.577632
Logistic Regression - l1 Regularization	0.628157	0.514749
Logistic Regression - l2 Regularization	0.732493	0.569231
Bernoulli Naive Bayes	0.622144	0.495792

Question 1g)

Bag of Words vs N-Gram Model

In [30]:
```
f1_scores_df = pd.DataFrame(f1_scores)
f1_scores_df.index = ['Train', 'Development']
f1_scores_df.index.name = 'F1 Scores - Bag of Words Model'
f1_scores_df.T
```

Out[30]:

F1 Scores - Bag of Words Model	Train	Development
Logistic Regression - No Regularization	0.950077	0.679651
Logistic Regression - L1 Regularization	0.833912	0.739514
Logistic Regression - L2 Regularization	0.859116	0.738729
Bernoulli Naive Bayes	0.792587	0.747440

The Bag of Words model outperform N-gram model across train and development sets, logistic regression, and Bernoulli Naive Bayes models.

The highest F1-score on the development set was 0.577 for the N-gram model and 0.747 for the Bag of Words model, indicating that the latter is better at predicting whether a tweet pertains to a real disaster or not.

The N-gram model is overfitting, as evidenced by the stark differences in F1 scores between training and development set. The Bag of Words model effectively captures the overall frequency of relevant words without the complications introduced by n-gram combinations. This implies that for the task of predicting whether a tweet pertains to a real disaster or not, capturing individual word frequencies (as in the Bag of Words model) is more effective than focusing on word combinations (as in the n-gram model). Moreover, since tweets are short, n-grams can lead to sparsity issues, as many word combinations might not appear frequently enough to be informative. With shorter texts like Tweets, the Bag of Words model is better suited.

Question 1i)

Determining performance on Kaggle test set

I will re-build my feature vectors and re-train on my preferred classifier (either bag of word or n-gramusing either logistic regression or Bernoulli naive bayes) using the entire Kaggle training data. Then, I will test it on the Kaggle test data.

In [31]:
```
train_set = preprocessing(train)
test_set = preprocessing(test)

M = 5  #based on mean and common NLP practices
vectorizer = CountVectorizer(binary=True, min_df=M)

X_train = vectorizer.fit_transform(train_set['text']).toarray()
y_train = train_set['target'].tolist()

X_test = vectorizer.transform(test_set['text']).toarray()
```

In [32]:
```
nb_classifier = BernoulliNaiveBayes(alpha=1.0)
nb_classifier.fit(X_train, y_train)

y_train_pred = nb_classifier.predict(X_train)
y_test_pred = nb_classifier.predict(X_test)

f1_train = f1_score(y_train, y_train_pred)

print(f"F1 Score on Kaggle Training Set using Bag of Words Model and Bernoulli Naive Bayes Classifier: {f1_train}")
```

```
F1 Score on Kaggle Training Set using Bag of Words Model and Bernoulli Naive Bayes Classifier: 0.7932135057953973
```

On the Kaggle training set, I have an F1 score of 0.793 using the Bag of Words model and Bernoulli Naive Bayes classifier. This matches my expectation, because it aligns with the F1 score I saw when I only used 70% of my training set.

On the Kaggle test set, I have an F1 score of 0.794 as seen in the image below. I expected the accuracy to be lower on my test set due to overfitting, but it perfectly aligns with the F1 score on my training set. It may be higher than expectation, because my model is good at generalizing patterns and predicting on unseen data. The test set may also be very similar to the training set, resulting in closely aligned scores. The organizers may ensure this distribution similarity for fair benchmarking.

Search

Natural Language Processing with Disaster Tweets

Predict which Tweets are about real disasters and which ones are not

Overview Data Code Models Discussion Leaderboard Rules Team Submissions

Submissions

All Successful Errors Recent

Submission and Description	Public Score
AtmikaPai_NLP_submission (2).csv Complete · now	0.79436
AtmikaPai_NLP_submission (1).csv Complete · 4m ago	0.72448
AtmikaPai_NLP_submission.csv Error · 5m ago	

Written Exercises

1) Regularization

a) The regularization term is incorrectly applied to the target variable (y) instead of weights (w). $||y||^2_2$ does not depend on w, as it is fixed. So the penalty is constant with respect to w. This has no effect on penalizing large weights and preventing overfitting, and so it does not accomplish regularization.

b) The purpose of regularization is to penalize large values of w by adding a positive regularization term to the loss function. A negative λ encourages larger weights, leading to a model that overfits on training data. This is the antithesis of regularization.

2) Overfitting and Underfitting

a) Classifier A has similar accuracy for both the training (72.3%) and testing (70.4%) sets, so it generalizes well to unseen data. Having said that, I think ~70% is a low accuracy rate for a spam mail detection model. Therefore, I think the model is underfitting and would benefit from more features and feature engineering.

b) Classifier C is overfitting since the training set accuracy (92.6%) is much higher than that of the train set (61.7%). This significant gap shows that the model has memorized patterns in the training data, but is not good at generalizing patterns nor predicting on unseen data. Classifier C has a higher training accuracy than Classifier A and B likely because it has a more expressive model class.

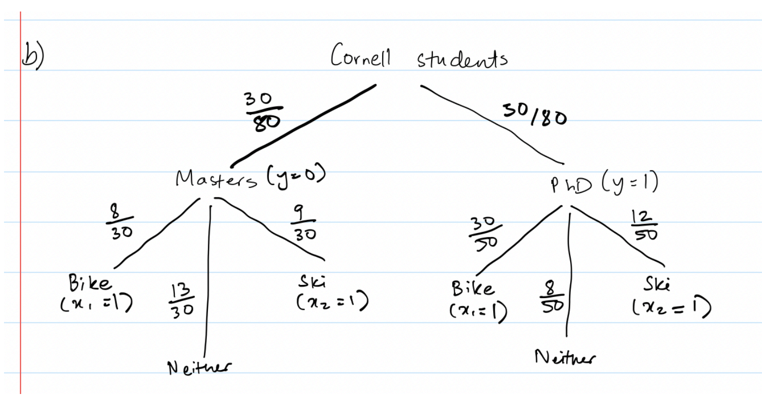
c) Underfitting usually occurs when the model is too simple or the features are insufficient. Classifier A has similar performance on training and test data, and it is underfitting as evidenced by the <80% accuracy rates. Improving performance would likely require a more expressive model class or better feature engineering rather than just adding more data. Hence, adding more training examples may not significantly improve accuracy.

Overfitting occurs when a model memorizes patterns and noise in the training data and fails to generalize on unseen data. Classifier C performs very well on the training data (92.6%), but much worse on the test data (61.6%). Retraining the model on a richer, bigger, and more diverse data set should improve its performance on the test set.

2) Naive Bayes with Binary Features

a) In this context, the Naive Bayes assumption means that the features x_1 (biking) and x_2 (skiing) are conditionally independent given the target class y (PhD or Master's student). In other words, the probability of biking and the probability of skiing are assumed to be independent from each other, given whether the student is a PhD or Master's student.

b)



$$P(y=0 \mid x_1=0, x_2=0) = \frac{P(x_1=0, x_2=0 \mid y=0) \cdot P(y=0)}{P(x_1=0, x_2=0)}$$

$$= \frac{\frac{13}{30} \times \frac{30}{80}}{\frac{21}{80}}$$

$$= \frac{13}{\cancel{30}} \times \frac{\cancel{30}}{\cancel{80}} \times \frac{\cancel{80}}{21}$$

$$= \frac{13}{21}$$

c) If every PhD who skis also bikes, then biking and skiing are not independent for PhD students. This violates the Naive Bayes assumption for PhD students. However, for Master's students, no such dependency exists, so we still assume independence. Hence, the probability calculation (question 2b) for Master's students does not change, as it only affects PhD students. (The new information does not change the denominator in our calculation of $P(x_1 = 0, x_2 = 0)$, because it doesn't change the count of those who neither bike nor ski.)

4) Categorical Naive Bayes

(I used Perplexity for this question, because I was unsure how to get the derivations.)
https://www.perplexity.ai/

a)

4a) Likelihood function: $L(\phi) = \prod_{i=1}^{n} P_\theta(y^{(i)})$ $\qquad P_\theta(y^{(i)} = k) = \phi_k$

$$\Rightarrow L(\phi) = \prod_{k=1}^{K} \phi_k^{n_k}$$

Log likelihood: $\log L(\phi) = \sum_{k=1}^{K} n_k \log \phi_k$

To maximize the log likelihood function, I will use the Lagrange multiplier with the constraint $\sum_{k=1}^{k} \phi_k = 1$ since probabilities need to sum to 1.

$$\mathcal{L}(\phi, \lambda) = \sum_{k=1}^{K} n_k \log \phi_k + \lambda\left(1 - \sum_{k=1}^{K} \phi_k\right)$$

Next, I will take partial derivatives:

$$\frac{\partial L}{\partial \phi_k} = \frac{n_k}{\phi_k} - \lambda = 0 \qquad \Rightarrow ① \; \phi_k = \frac{n_k}{\lambda}$$

$$\sum_{k=1}^{K} \phi_k = 1 \quad \Rightarrow \quad \sum_{k=1}^{k} \frac{n_k}{\lambda} = 1 \quad \Rightarrow \quad \sum_{k=1}^{k} n_k = \lambda \quad \Rightarrow ② \quad n = \lambda$$

Putting ① and ② together, $\phi_k^* = \dfrac{n_k}{n}$

b)

b) Likelihood function: $L(\psi) = \prod_{j=1}^{d} \prod_{l=1}^{L_j} \psi_{jkl}^{n_{jkl}}$ → Number of times feature x_j takes value l in class k

Log likelihood: $\log L(\psi) = \sum_{j=1}^{d} \sum_{l=1}^{L_j} n_{jkl} \log \psi_{jkl}$

To maximize the log likelihood function, I will use the Lagrange multiplier with the constraint $\sum_{l=1}^{L_j} \psi_{jkl} = 1$ since probabilities need to sum to 1.

$$\mathcal{L} = \sum_{j=1}^{d} \sum_{l=1}^{L_j} n_{jkl} \log \psi_{jkl} + \sum_{j=1}^{d} \lambda_j \left(1 - \sum_{l=1}^{L_j} \psi_{jkl}\right)$$

Next, I will take partial derivatives:

$$\frac{\partial \mathcal{L}}{\partial \psi_{jkl}} = \frac{n_{jkl}}{\psi_{jkl}} - \lambda_j = 0 \Rightarrow ① \; \psi_{jkl} = \frac{n_{jkl}}{\lambda_j}$$

$$\sum_{l=1}^{L_j} \psi_{jkl} = 1 \Rightarrow \sum_{l=1}^{L_j} \frac{n_{jkl}}{\lambda_j} = 1 \Rightarrow \sum_{l=1}^{L_j} n_{jkl} = \lambda_j \Rightarrow ② \; n_k = \lambda_j$$

Putting ① and ② together, $\psi^*_{jkl} = \frac{n_{jkl}}{n_k}$