Assignment 2: Sentiment Classification Using Logistic Regression

Programming Assignment (100 Points scaled to 40)

For this assignment we will be implementing a naive bayes baseline classifier. Additionally, we will be using pytorch to implement a binary logistic regression classifier. Our task is sentiment classification for hotel reviews. The input to your model will be a text review, and the output label is a 1 or 0 marking it as positive or negative.

We have provided a util.py file for loading the data, and some of the basic modeling. Your task is to fill in the functions below in order to train as accurate a classifier as possible!

We suggest browsing the util.py script first. Additionally, make sure to install dependencies from the provided requirements.txt file in a similar fashion to the pytorch tutorial. With your environment activated int he terminal, run:

```
pip install -r requirements.txt
```

In [30]:
```python
from typing import List
import spacy
import torch
import random
```

Section 1: Sentiment Classification Dataset (Total: 20 Points)

The training data for this task consists of a collection of short hotel reviews. The data is formatted as one review per line. Each line starts with a unique identifier for the review (as in ID-2001) followed by tab and the text of the review. The reviews are not tokenized or sentence segmented in any way (the words are space separated). The positive reviews and negative reviews appear in separate files namely hotelPosT-train.txt and hotelNegT-train.txt.

In [37]:
```python
from util import load_train_data
pos_datapath = "data/hotelPosT-train.txt"
neg_datapath = "data/hotelNegT-train.txt"
all_texts, all_labels = load_train_data(pos_datapath, neg_datapath)
```

Lets look at what is in the data

In [40]:
```python
def random_sample(texts, labels, label):
    data_by_label = {}
    for lab, text in zip(labels, texts):
        if lab not in data_by_label:
            data_by_label[lab] = []
        data_by_label[lab].append(text)
    return random.choice(data_by_label[label])

print("--- Positive Example ---")
print(random_sample(all_texts, all_labels, label=1))
print("\n--- Negative Example ---")
print(random_sample(all_texts, all_labels, label=0))
```

```
--- Positive Example ---
I have no complaints and I'm a picky hotel guest. The room was clean, the sheets were not old, and the bathroom
was spotless. Everything worked properly which made for a great experience while getting ready for an intervie
w. The front desk staff was more the helpful. They gave us advice on where to eat, information on the city, and
the place I was interviewing at. The continental breakfast had lots of unique options; it went beyond the avera
ge spread at a hotel. I'm impressed.

--- Negative Example ---
I went to Syracuse last winter to watch my team play in the Carrier Dome and chose this Econo Lodge because the
prices were cheaper (because I found out later that it's in a pretty run-down part of town) and mainly cause mo
st of the better hotels were already booked. I drove up there and arrived pretty late, so I was very tired and
ready to get some sleep before the game the next day. After pulling into the small parking lot, I realized afte
r driving around that all the Free Parking spaces were gone, so I had to drive down the street to a paid parkin
g lot. Then, after carrying my luggage all the way to the hotel, I checked in and, in a sleepy haze, threw my s
tuff down in the room and went to sleep.Not more than two hours later, I woke up from incredible itching on my
arms and legs, so I quickly turned on the light and realized how awfully dirty my room was. Then I looked close
r at my bed near the sheets and I literally could see many, if not hundreds, of tiny bedbugs crawling everywher
e. I immediately ran to the desk, where no one was there of course, and after waiting for 30 minutes for someon
e to show up, I demanded another room. I then got the new room key, went up to it, and after opening the door,
I saw that this new room was no more clean than the last. And yes, there were just as many bedbugs in this bed.
I grabbed my stuff and walked back to my car and slept there for the rest of the night. Needless to say, not on
ly will I never visit this Econo Lodge again, I doubt I will ever even visit Syracuse again.
```

Test Data (WAIT TILL DEADLINE)

This is the test dataset that you will need to use to report the results on. This set is the unseen dataset meaning, you are not in anyway supoose to look what is in this dataset. We will release this dataset on the last day of the assignment's deadline.

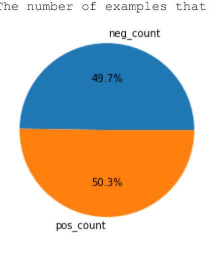
In [45]:
```python
### RUN THIS ONLY ON DEADLINE ###
# Load the test data

from typing import List, Tuple, Any


def load_test_data(filepath: str) -> tuple[list[Any], list[Any]]:
    """Load the test data, producing a List of texts, labels

    Args:
        filepath (str): Path to the training file

    Returns:
        tuple[list[Any], list[Any]]: The texts and labels
    """
    lab_map = {'POS': 1, 'NEG': 0}
    texts = []
    labels = []
    with open(filepath, "r") as file:
        for line in file:
            idx, text, label = line.rstrip().split("\t")
            texts.append(text)
            labels.append(lab_map[label])

    return texts, labels


test_texts, test_labels = load_test_data('./data/HW2-testset.txt')
```

Task 1.1: Print the number of "positive" and "negative" samples (5 Points)

It is important to know the distribution of the training examples. More often than not, you will have to work with datasets that are not "balanced" with respect to the labels of the samples. For this task, print out the number of examples that have label = 1 and label = 0, respectively, in std:out or plot a pie chart.

In [41]:
```python
### ENTER CODE HERE ###
import matplotlib.pyplot as plt
import numpy as np
# Note since we have them in two seperate files,
# this can also be done with bash commands
def label_distribution(labels):
    """
    TODO: Replace the line `raise NotImplementedError` with your code
    to print the labels distribution.
    """
    neg_count = pos_count = 0
    for num in labels:
        if num == 0:
            neg_count+=1;
        elif num == 1:
            pos_count+=1;
    print("The number of examples that have label = 0: ", neg_count)
    print("The number of examples that have label = 1: ", pos_count)

    y = np.array([neg_count, pos_count])
    mylabels = ["neg_count", "pos_count"]

    plt.pie(y, labels = mylabels, autopct='%.1f%%')
    plt.show()

label_distribution(all_labels)
```

```
The number of examples that have label = 0:  94
The number of examples that have label = 1:  95
```

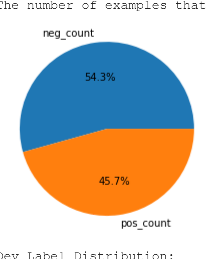


Task 1.2: Split Training and Development Sets (5 Points)

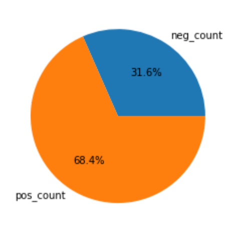
For the purpose of coming with the best parameters for the model you will have to split the dataset into training and development sets. Make sure the splits follow the same distribution.

In [47]:
```python
### ENTER CODE HERE ###
import numpy as np
import pandas as pd
def split_dataset(texts, labels):
    """
    Split the dataset randomly into 80% training and 20% development set
    Make sure the splits have the same label distribution
    """
    indices = list(range(len(texts)))
    num_training_indices = int(0.8 * len(texts))
    np.random.shuffle(indices)
    train_indices = indices[:num_training_indices]
    dev_indices = indices[num_training_indices:]
    # split the actual data
    train_texts, train_labels = texts.iloc[train_indices], labels.iloc[train_indices]
    dev_texts, dev_labels = texts.iloc[dev_indices], labels.iloc[dev_indices]
    return train_texts[0].values.tolist(), train_labels[0].values.tolist(), dev_texts[0].values.tolist(), dev_l

train_texts = pd.DataFrame(all_texts)
train_labels = pd.DataFrame(all_labels)

train_texts, train_labels, dev_texts, dev_labels = split_dataset(train_texts, train_labels)

print('Train Label Distribution:')
label_distribution(train_labels)

print('Dev Label Distribution:')
label_distribution(dev_labels)
```

```
Train Label Distribution:
The number of examples that have label = 0:  82
The number of examples that have label = 1:  69
```




```
Dev Label Distribution:
The number of examples that have label = 0:  12
The number of examples that have label = 1:  26
```



Task 1.3: Evaluation Metrics (10 Points)

Implement the evaulation metrics: Accuracy, Precision, Recall and F1 score

In [6]:
```python
### ENTER CODE HERE ###

def accuracy(predicted_labels, true_labels):
    """
    Accuracy is correct predictions / all predicitons
    """
    correct = 0
    for i in range(len(true_labels)):
        if predicted_labels[i] == true_labels[i]:
            correct += 1
    return correct / len(true_labels)

def precision(predicted_labels, true_labels):
    """
    Precision is True Positives / All Positives Predictions
    """
    TP = 0
    for i in range(len(true_labels)):
        if predicted_labels[i] == true_labels[i] and true_labels[i] == 1:
            TP += 1
    return TP / sum(predicted_labels)


def recall(predicted_labels, true_labels):
    """
    Recall is True Positives / All Positive Labels
    """
    TP = 0
    for i in range(len(true_labels)):
        if predicted_labels[i] == true_labels[i] and true_labels[i] == 1:
            TP += 1
    return TP / sum(true_labels)

def f1_score(predicted_labels, true_labels):
    """
    F1 score is the harmonic mean of precision and recall
    """
    prec = precision(predicted_labels, true_labels)
    reca = recall(predicted_labels, true_labels)
    return 2 * prec * reca / (prec + reca)
```

Section 2: Baselines (Total: 20 Points)

It is important to come up with baselines for the classifications to compare the more complicated models with. The baselines are also useful as a debugging method for your actual classfication model. You will create two baselines:

1. Random Chance
2. Naive Bayes Classifier

Task 2.1: Random Chance Classifier (5 Points)

A random chance classifier predicts the label according to the label's distribution. As an example, if the label 1 appears 70% of the times in the training set, you predict 70 out of 100 times the label 1 and label 0 30% of the times

In [7]:
```python
### ENTER CODE HERE ###

def predict_random(train_labels, num_samples):
    result = np.random.choice([0, 1], size=num_samples,
                    p=[1 - (sum(train_labels)/len(train_labels)), sum(train_labels)/len(train_labels)])
    return result
```

Task 2.2: Naive Bayes Classifier (Total: 10 Points)

In the class, Jim went over how to implement a Naive Bayes Classifier using the tokens in the training samples. In this task, you will do the same. As a preprocessing step, you might want to remove the stop words and lemmatize/stem the words of the texts.

Spacy Model https://spacy.io

To tokenize the text and help extract features from text, we will use the popular spaCy model

In [8]:
```python
### DO NOT EDIT ###

# Initialize the spacy model
nlp = spacy.load('en_core_web_sm')
```

Task 2.2.1: Play around with spacy (0 Points)

In [9]:
```python
### ENTER CODE HERE ###

test_string = "This is an amazing sentence"

# parse the string with spacy model
test_doc = nlp(test_string)

print('Token', 'Lemma', 'Is_Stopword?')
for token in test_doc:
    print(token, token.lemma_, token.is_stop)
```

```
Token Lemma Is_Stopword?
This this True
is be True
an an True
amazing amazing False
sentence sentence False
```

Task 2.2.2: Preprocessing (5 Points)

Remove stopwords and lemmatize the words of a text

In [10]:
```python
### ENTER CODE HERE ###

def pre_process(text: str) -> List[str]:
    """
    remove stopwords and lemmatize and return an array of lemmas
    """
    my_doc = nlp(text)

    lemma_nonstop = []

    for token in my_doc:
        if token.is_stop == False:
            lemma_nonstop.append(token.lemma_)
    return lemma_nonstop

test_string = "This sentence needs to be lemmatized"

assert len({'sentence', 'need', 'lemmatize', 'lemmatiz'}.intersection(pre_process(test_string))) >= 3

print('All Test Cases Passed!')
```

```
All Test Cases Passed!
```

Task 2.2.3: The Naive Bayes Class (5 Points)

The standard way of implementing classifiers like Naive Bayes is to implement the two methods: "fit" and "predict". The fit method expects the training data along with labels, and the predict method predicts the labels for the provides texts of samples.

In [24]:
```python
### ENTER CODE HERE ###
import operator
import math
class NaiveBayesClassifier:
    def __init__(self, num_classes):
        self.num_classes = num_classes
        self.label_words_count_pos = dict()
        self.label_words_count_neg = dict()

    def fit(self, texts, labels):
        """
        1. Group samples by their labels
        2. Preprocess each text
        3. Count the words of the text for each label
        """

        for i in range(len(texts)):

            vector = texts[i]
            class_value = int(labels[i])

            words = pre_process(vector)

            if (class_value == 1):
                for word in words:
                    self.label_words_count_pos[word] = self.label_words_count_pos.get(word, 0) + 1
            elif (class_value == 0):
                for word in words:
                    self.label_words_count_neg[word] = self.label_words_count_neg.get(word, 0) + 1

    def predict(self, texts):
        """
        1. Preprocess the texts
        2. Predict the class by using the likelihood with Bayes Method and Laplace Smoothing
        """

        pos_count_sum = sum(self.label_words_count_pos.values())
        neg_count_sum = sum(self.label_words_count_neg.values())

        label_words_prob_pos = self.label_words_count_pos.copy()
        label_words_prob_neg = self.label_words_count_neg.copy()

        label_words_prob_pos = {key: value / pos_count_sum for key, value in label_words_prob_pos.items()}
        label_words_prob_neg = {key: value / neg_count_sum for key, value in label_words_prob_neg.items()}

        result = []

        for i in range(len(texts)):

            vector = texts[i]
            words = pre_process(vector)

            pos_score = 0
            neg_score = 0

            for word in words:

                if word in self.label_words_count_pos:
                    pos_score += math.log(label_words_prob_pos[word])
                elif word not in self.label_words_count_pos:
                    pos_score += math.log(float(1/pos_count_sum))

                if word in self.label_words_count_neg:
                    neg_score += math.log(label_words_prob_neg[word])
                elif word not in self.label_words_count_neg:
                    neg_score += math.log(float(1/neg_count_sum))

            if pos_score > neg_score:
                result.append(1)
            else:
                result.append(0)

        return result
```

Task 2.3: Baseline Results (5 Points)

Since there is not hyperparameter-tuing required for the baselines, we can use the entirety of the training set (no need to split the dataset into train and development). Report the results you achieve with the two baselines by running the following cell:

In [12]:
```python
### DO NOT EDIT ###

### DEV SET RESULTS
testset_prediction_random = predict_random(train_labels, num_samples=len(dev_labels))
print('Random Chance F1:', f1_score(testset_prediction_random, dev_labels))

naive_bayes_classifier = NaiveBayesClassifier(num_classes=2)
naive_bayes_classifier.fit(train_texts, train_labels)
testset_predictions_nb = naive_bayes_classifier.predict(dev_texts)
print('Naive Bayes F1:', f1_score(testset_predictions_nb, dev_labels))
```

```
Random Chance F1: 0.5945945945945946
Naive Bayes F1: 0.9090909090909091
```

In [27]:
```python
### DO NOT EDIT ###
### RUN THIS ONLY ON DEADLINE ###
### TEST SET RESULTS

testset_prediction_random = predict_random(all_labels, num_samples=len(test_labels))
print('Random Chance F1:', f1_score(testset_prediction_random, test_labels))

naive_bayes_classifier = NaiveBayesClassifier(num_classes=2)
naive_bayes_classifier.fit(all_texts, all_labels)
testset_predictions_nb = naive_bayes_classifier.predict(test_texts)
print('Naive Bayes F1:', f1_score(testset_predictions_nb, test_labels))
```

```
Random Chance F1: 0.4912280701754386
Naive Bayes F1: 0.9019607843137256
```

Section 3: Logistic Regression on Features (Total: 60 Points)

Now let's try building a logistic regression based classifier on hand-engineered features.

The following tasks are going to be the implementation of the components required in building a Logistic Regressor.

Task 3.0: Feature Extraction (20 points)

This is perhaps the most challenging part of this assignment. In the class, we went over how to featurize text for a classification system for sentiment analysis. In this assignment, you should implement and build upon this to accuractely classify the hotel reviews.

This task requires a thorough understanding of the dataset to answer the important question, "What is in the data?". Please go through some of the datapoints and convert the signals that you think might help in identifying "sentiment" as features.

Please refer to the section in Jim's book that illustrates the process of feature engineering for this task. We have attached an image of the table below:

Var	Definition	Value in Fig. 5.2
x_1	count(positive lexicon) $\in$ doc)	3
x_2	count(negative lexicon) $\in$ doc)	2
x_3	$\begin{cases} 1 & \text{if "no"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$	1
x_4	count(1st and 2nd pronouns $\in$ doc)	3
x_5	$\begin{cases} 1 & \text{if "!"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$	0
x_6	log(word count of doc)	$\ln(64) = 4.15$

Please use the files with postive and negative words attached in the assignment: positive_words.txt and negative_words.txt

In [13]:
```python
from util import load_train_data
pos_datapath = "data/positive-words.txt"
neg_datapath = "data/negative-words.txt"

my_file = open(pos_datapath, "r")
content = my_file.read()
pos_lex = content.split("\n")
my_file.close()

my_file = open(neg_datapath, "r")
content = my_file.read()
neg_lex = content.split("\n")
my_file.close()

def make_test_feature_1(text: spacy.tokens.doc.Doc):
    count = 0
    for t in text:
        tem = t.lemma_
        if t.lemma_ in pos_lex:
            count += 1
    return count

def make_test_feature_2(text: spacy.tokens.doc.Doc):
    count = 0
    for t in text:
        if t.lemma_ in neg_lex:
            count += 1
    return count

def make_test_feature_3(text: spacy.tokens.doc.Doc):
    count = 0
    for t in text:
        if t.lemma_ == 'no':
            count += 1
    return count

def make_test_feature_4(text: spacy.tokens.doc.Doc):
    count = 0
    pronouns = ['I', 'me', 'my', 'My' , 'mine', 'myself', 'You', 'you', 'your', 'Your', 'yours', 'yourself']
    for t in text:
        if t.lemma_ in pronouns:
            count += 1
    return count

def make_test_feature_5(text: spacy.tokens.doc.Doc):
    count = 0
    for t in text:
        if t.lemma_ == '!':
            count += 1
    return count

def make_test_feature_6(text: spacy.tokens.doc.Doc):
    count = 0
    for t in text:
        count += 1
    return np.log(count)


def extract_features(text: spacy.tokens.doc.Doc):
    features = []
    # TODO: Replace this with your own feature extraction functions.
    # TODO: add more features to the feature vector
    features.append(make_test_feature_1(text))
    features.append(make_test_feature_2(text))
    features.append(make_test_feature_3(text))
    features.append(make_test_feature_4(text))
    features.append(make_test_feature_5(text))
    features.append(make_test_feature_6(text))

    return features
```

In [14]:
```python
### ENTER CODE HERE ###
### DO NOT CHANGE THE SIGNATURE OF THE function THOUGH ###

def featurize_data(texts, labels):
    features = [
        extract_features(doc) for doc in nlp.pipe(texts)
    ]
    return torch.FloatTensor(features), torch.FloatTensor(labels)
```

Task 3.0.2: Feature Scaling (10 Points)

In this task we will use the data normalization technique to ensure the scales of the feature are consistent. After featurizing the dataset, we need to call the following function before passing it to the classifier

Normalization Formula

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

In [15]:
```python
### ENTER CODE HERE ###

def normalize(features: torch.Tensor) -> torch.Tensor:
    """
    return the features transformed by the above formula of normalization
    """
    feature_min = torch.min(features)
    feature_max = torch.max(features)
    for row in range(features.shape[0]):
        for col in range(features.shape[1]):
            features[row][col] = (features[row][col].item() - feature_min) / (feature_max - feature_min)
    return features
```

Training a Logistic Regression Classifier (Total: 30 Points)

In this section, you will implement the components needed to train the binary classifier using logistic regression

Here we define our pytorch logistic regression classifier (DO NOT EDIT THIS)

In [16]:
```python
class SentimentClassifier(torch.nn.Module):
    def __init__(self, input_dim: int):
        super().__init__()
        # We force output to be one, since we are doing binary logistic regression
        self.output_size = 1
        self.coefficients = torch.nn.Linear(input_dim, self.output_size)
        # Initialize weights. Note that this is not strictly necessary,
        # but you should test different initializations per lecture
        initialize_weights(self.coefficients)

    def forward(self, features: torch.Tensor):
        # We predict a number by multipling by the coefficients
        # and then take the sigmoid to turn the score as logits
        return torch.sigmoid(self.coefficients(features))
```

Task 3.1: Initialize the weights. (5 Points)

Initialization of the parameters is an important step to ensure the SGD algorithm converges to a global optimum. Typically, we need to try different initialization methods and compare the accuracy we achieve for the development set. In this task, implement the function that initializes the parameters to ...

In [17]:
```python
### ENTER CODE HERE ###
import math
def initialize_weights(coefficients):
    """
    TODO: Replace the line `raise NotImplementedError` with your code.
    Initialize the weights of the coefficients by assigning the parameter
    coefficients.weights.data = ...
    """
    return torch.nn.init.xavier_uniform_(coefficients.weight)
```

Let's build a training function similar to the linear regressor from the tutorial

Task 3.2: Logistic Loss Function (10 Points)

In [18]:
```python
### ENTER CODE HERE ###

def logistic_loss(prediction: torch.Tensor, label: torch.Tensor) -> torch.Tensor:
    """
    TODO: Implement the logistic loss function between a prediction and label.
    """
    l1 = torch.nn.BCEWithLogitsLoss()
    return l1(prediction, label)
```

Task 3.3: Create an SGD optimizer (0 Points)

We have already provided the implementation of how to create the SGD optimizer

You may try different optimizers refering to the docs provided

In [19]:
```python
### ENTER CODE HERE ###

def make_optimizer(model, learning_rate) -> torch.optim:
    """
    Returns an Stocastic Gradient Descent Optimizer
    See here for algorithms you can import: https://pytorch.org/docs/stable/optim.html
    """
    return torch.optim.SGD(model.parameters(), learning_rate)
```

Task 3.5: Converting Logits into Predictions (5 Points)

In [20]:
```python
### ENTER CODE HERE ###

def predict(model, features):
    with torch.no_grad():
        """
        TODO: Replace the line `raise NotImplementedError`
        with the logic of converting the logits into prediction labels (0, 1)
        """
        logits = model(features)
        return torch.round(logits)
```

Training Function (DO NOT EDIT THIS)

In [21]:
```python
### DO NOT EDIT ###

from tqdm.autonotebook import tqdm
import random


def training_loop(
    num_epochs,
    batch_size,
    train_features,
    train_labels,
    dev_features,
    dev_labels,
    optimizer,
    model
):
    samples = list(zip(train_features, train_labels))
    random.shuffle(samples)
    batches = []
    for i in range(0, len(samples), batch_size):
        batches.append(samples[i:i+batch_size])
    print("Training...")
    for i in range(num_epochs):
        losses = []
        for batch in tqdm(batches):
            # Empty the dynamic computation graph
            features, labels = zip(*batch)
            features = torch.stack(features)
            labels = torch.stack(labels)
            optimizer.zero_grad()
            # Run the model
            logits = model(features)
            # Compute loss
            loss = logistic_loss(torch.squeeze(logits), labels)
            # In this logistic regression example,
            # this entails computing a single gradient
            loss.backward()
            # Backpropogate the loss through our model

            # Update our coefficients in the direction of the gradient.
            optimizer.step()
             # For logging
            losses.append(loss.item())

        # Estimate the f1 score for the development set
        dev_f1 = f1_score(predict(model, dev_features), dev_labels)
        print(f"epoch {i}, loss: {sum(losses)/len(losses)}")
        print(f"Dev F1 {dev_f1}")

    # Return the trained model
    return model
```

Task 3.6: Train the classifier (10 Points)

Run the following cell to train a logistic regressor on your hand-engineered features.

In [52]:
```python
num_epochs = 500

train_features, train_labels_tensor = featurize_data(train_texts, train_labels)
train_features = normalize(train_features)
dev_features, dev_labels_tensor = featurize_data(dev_texts, dev_labels)
dev_features = normalize(dev_features)
model = SentimentClassifier(train_features.shape[1])
optimizer = make_optimizer(model, learning_rate=0.5)

trained_model = training_loop(
    num_epochs,
    16,
    train_features,
    train_labels_tensor,
    dev_features,
    dev_labels_tensor,
    optimizer,
    model
)
```

```
Training...
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epoch 0, loss: 0.7417197108268738
Dev F1 tensor([0.3226])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 1, loss: 0.7333073854446411
Dev F1 tensor([nan])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 2, loss: 0.7263218641281128
Dev F1 tensor([nan])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 3, loss: 0.7206681430339813
Dev F1 tensor([nan])
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epoch 4, loss: 0.7161434412002563
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epoch 5, loss: 0.7125257790088654
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epoch 6, loss: 0.7096173286437988
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epoch 7, loss: 0.7072575688362122
Dev F1 tensor([nan])
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epoch 8, loss: 0.705322003364563
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epoch 9, loss: 0.7037158846855164
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epoch 10, loss: 0.7023677825927734
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epoch 11, loss: 0.701223623752594
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  0%|          | 0/10 [00:00<?, ?it/s]
epoch 482, loss: 0.6152577519416809
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 483, loss: 0.6151879310607911
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 484, loss: 0.6151182770729064
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 485, loss: 0.6150488734245301
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 486, loss: 0.6149796485900879
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 487, loss: 0.6149106681346893
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 488, loss: 0.614841878414154
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 489, loss: 0.614773279428482
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 490, loss: 0.6147048950195313
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 491, loss: 0.6146367490291595
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 492, loss: 0.6145687401294708
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 493, loss: 0.6145009815692901
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 494, loss: 0.6144334256649018
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 495, loss: 0.6143660366535186
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 496, loss: 0.6142988502979279
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 497, loss: 0.6142318964004516
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 498, loss: 0.6141651332378387
Dev F1 tensor([0.8750])
  0%|          | 0/10 [00:00<?, ?it/s]
epoch 499, loss: 0.6140985250473022
Dev F1 tensor([0.8750])
```

Task 3.7: Get the predictions on the Test Set using the Trained model and print the F1 score (10 Points)

In [50]:

```python
### DO NOT EDIT ###

### DEV SET RESULTS

dev_features, dev_labels = featurize_data(dev_texts, dev_labels)
print('Logistic Regression Results:')
print('Accuracy:', accuracy(predict(trained_model, dev_features), dev_labels))
print('F1-score', f1_score(predict(trained_model, dev_features), dev_labels))
```

```
Logistic Regression Results:
Accuracy: 0.868421052631579
F1-score tensor([0.9057])
```

In [51]:

```python
### DO NOT EDIT ###
### RUN THIS ONLY ON DEADLINE ###
### TEST SET RESULTS

test_features, test_labels = featurize_data(test_texts, test_labels)
print('Logistic Regression Results:')
print('Accuracy:', accuracy(predict(trained_model, test_features), test_labels))
print('F1-score', f1_score(predict(trained_model, test_features), test_labels))
```

```
Logistic Regression Results:
Accuracy: 0.84
F1-score tensor([0.8621])
```

Written Assignment (60 Points)

Written assignment tests the understanding of the student for the assignment's task. We have split the writing into sections. You will need to write 1-2 paragraphs describing the sections. Please be concise.

In your own words, describe what the task is (20 points)

Describe the task, how is it useful and an example.

Section 1: Sentiment Classification Dataset:

We have two datasets of a collection of hotel reviews (positive and negative), both datasets are one review per line. The reviews are not tokenized, or sentence segmented, and the words are space separated. We need to explore the distribution of the reviews (positive and negative), create training and test datasets (split the original dataset), and define functions for evaluation metrics (compute accuracy, precision, recall, and f1 score)

Section 2: Baselines:

We need to create two baselines for Random Chance and Naïve Bayes Classifier. The Random Chance predict the label according to the labels' distribution. The Naïve Bayes Classifier using tokens in the training samples. We need preprocess the set and implement fit and predict methods. We will compare these two baselines by f1 score on same sample set.

Section 3: Logistic Regression on Features:

We need to build a logistic regression based on hand-engineered features. We need to implement feature extraction to featurize text for a classification system for sentiment analysis. We need to have a normalization formula to normalize dataset for control the scales before passing it to the classifier. We need to implement weights and logistic loss function and convert logits into prediction functions. We need to use different epochs and learning rate to improve the result.

Describe your method for the task (10 points)

Important details about the implementation. Feature engineering, parameter choice etc.

Section 1: Sentiment Classification Dataset:

We use util.py to load the dataset. We use a for-loop to iterate items in labels: whenever we get label == 0, we increase negative count by one, same logic for positive reviews. I use pie chart for visualization. For split the dataset, I transform the list object into DataFrame first, then shuffle indices using numpy.random.shuffle to split the dataset randomly. I use DataFrame.values.tolist() to transform DataFrame back to list object.

For evaluation metrics, we use a for-loop to compare values between predicted_labels and true_labels, whenever we get same values equal to 1, we increase TP (true positive) by 1. Accuracy (correct prediction / all prediction), Precision (True Positive / All Positive Prediction), Recall (True Positive / All Positive Labels), and F1 Score (2 *Precision* Recall / (Recall + Precision))

Section 2: Baselines:

I use NumPy library to randomly generate value set based on training distributions. I use spacy to tokenize the text and help extract features from text. I preprocess text using lemma_ function and remove stopwords using is_stop function.

The fit method for Naïve Bayes Classifier I need to group samples by their labels and preprocess each text. I count the words of the text for each label through a for-loop and dictionary, whenever we get a word, we update the dictionary. The predict method for Naïve Bayes Classifier I need to compute each word probability by calculate the count of that word divided by whole word count. I use LaPlace smoothing, whenever I get a new word not in the training dictionary, I add 1 to it. I use math.log to sum all probability, return result by compared positive probability and negative probability.

Section 3: Logistic Regression on Features:

I implement six features exactly showed in the table: count (positive/negative lexicon), count (1st and 2nd pronouns), add 1 if get 'no' or '!', and log(word count of doc). Normalize torch.Tensor by iterating a 2D array and update values based on the formula. I initialize the weight using built-in library in torch, which is torch.nn.init.xavier*uniform*. I use built-in library in torch to implement logistic loss function, which is torch.nn.BCEWithLogitsLoss. I convert logits into prediction by using built-in library torch, which is torch.round.

Experiment Results (10 points)

Typically a table summarizing all the different experiment results for various parameter choices

Section 1: Sentiment Classification Dataset:

All dataset

# of examples have label = 0	# of examples have label = 1
94	95

Train Label Distribution

# of examples have label = 0	# of examples have label = 1
74	77

Dev Label Distribution

# of examples have label = 0	# of examples have label = 1
20	18

Section 2: Baselines:

Dev Set Result

Random Chance F1	Naïve Bayes F1
0.5945945945945946	0.9090909090909091

Test Set Result (Deadline)

Random Chance F1	Naïve Bayes F1
0.491228	0.90196

Section 3: Logistic Regression on Features:

With Epoch = 500 and learning rate = 0.5
Dev Set Result at Epoch 500

Loss	F1
0.60735	0.9412

Dev Set Result/Logistic Regression Results

Accuracy	F1-score tensor
0.868421052631579	0.9057

Test Set Result/Logistic Regression Results (Deadline)

Accuracy	F1-score tensor
0.84	0.8621

Discussion (20 points)

Key takeaway from the assignment. Why is the method good? shortcomings? how would you improve? Additional thoughts?

Section 1: Sentiment Classification Dataset:

Use pie chart to visualize the distribution of positive and negative reviews. Although there are many other kinds of charts to explore the distribution, pie chart is the most intuitive ways for distribution. Use pandas library to split the dataset into training and test set by random shuffle the indices. However, there are many other ways to split the dataset but I'm more experience with pandas rather to transform original list object into DataFrame object than try other methods. Implement the evaluation metrics based on formula helps me to further understand accuracy, precision, recall and f1 score. I believe there are some libraries can automatically compute these values.

Section 2: Baselines:

Use numpy.random.choice to generate 0 and 1's based on distribution. Understand how to use spacy to remove stop words and tokenize sentences into words. Dictionary is quite useful when I implement fit method in Naïve Bayes Classifier. I update dictionary for counting whenever I iterate a word in the sentence. The predict method I need to create another two dictionaries for probability of each word from previous counting dictionary. The Laplace smoothing method helps us to calculate probability when the word is not in our dictionary. I use log function because sum all log is much faster than multiple all the probabilities.

Section 3: Logistic Regression on Features:

Use three built-in library in torch.tensor to initialize weights, logistic loss function, and covert logits into predictions. Try different combination of epoch and learning rate to get relatively good performance. In this assignment I only use one method to initialize weights and there are many more other built-in function to initialize weights that maybe can improve the result. On the other hand, I can implement more engineering features to improve feature extraction. For example, the count of third pronouns in the whole text, the count of comma in the whole text, and etc. The combination of epochs and learning rate can be tuned using exist library for parameter tuning.