HomeWork_1_CSE517

1 Text Classification – Eisenstein 4.6 (p. 89)

After you run tar -xzf A1.tgz, in the directory review polarity, you will find a dataset of positively and negatively classified reviews that was used by Pang and Lee [2], a seminal paper about sentiment classification. Consult the readme file for more information. Hold out a randomly selected 400 reviews as a test set.

```
In [38]:

1 import numpy as np
2 import matplotlib.pyplot as plt
3 import pandas as pd
4 from math import sqrt
```

In this step below the text files from the pos folder are being read and has been transformed into dataframe (df_pos). This datapframe contains two columns namely "Reviews" and "Sentiments (with values 'Positive')".

```
In [39]:
             # Import Module
           1
           2
             import os
           3
             # Folder Path
             path = r'/Users/nehakardam/Documents/UWclasses /CSE NLP/A1/A1 data/revi
           7
             # Change the directory
           8
             os.chdir(path)
             # Read text File
          10
          11
             def read text file(file path):
                 with open(file path, 'r') as f:
          12
          13
                      return f.read().splitlines()
          14
             # iterate through all file
          15
             collection of data pos = []
          17
             for file in os.listdir():
          18
                  # Check whether file is in text format or not
                 if file.endswith(".txt"):
          19
          20
                      file path = f"{path}/{file}"
                      # call read text file function
          21
          22
                      collection of data pos = collection of data pos + read text fil
```

In this step below the text files from the neg folder are being read and has been transformed into dataframe (df_pos). This datapframe contains two columns namely "Reviews" and "Sentiments (with values 'Negative')".

Reviews Sentiments

```
In [41]:
             # Folder Path
             path = r'/Users/nehakardam/Documents/UWclasses /CSE NLP/A1/A1 data/revi
           2
           3
           4
             # Change the directory
             os.chdir(path)
           7
             # iterate through all file
             collection of data neg = []
             for file in os.listdir():
                 # Check whether file is in text format or not
          10
                 if file.endswith(".txt"):
          11
                     file_path = f"{path}/{file}"
          12
                     # call read text file function
          13
          14
                     collection of data neg = collection of data neg + read text fil
In [42]:
            df_neg = pd.DataFrame(collection_of_data_neg, columns = ['Reviews'])
           2 df neg['Sentiments'] = 'Negative'
In [43]:
             #both the dataframe of positive and negative reviews are concatinated t
            df pos neg = [df pos, df neg]
           3 Collection_of_data = pd.concat(df_pos_neg)
           4 #Shuffle the columns of the data
           5 All data= Collection of data.sample(frac=1).reset index(drop=True)
           6 All data
```

Out[43]:

	neviews	Sentiments
0	whew . okay .	Negative
1	warning : this review contains some spoilers f	Positive
2	its nice to see a pg rated movie out at christ	Positive
3	he gives each one a different series of cranky	Negative
4	but like everything else , tarantino takes thi	Positive
64715	everything about this movie was just completel	Negative
64716	basically , he says , it boils down to a lack \dots	Negative
64717	$\ensuremath{y}\xspace^{\ensuremath{k}\xspace}$, that just sends chills down my spine .	Negative
64718	bryan singer's " the usual suspects " for one	Negative
64719	i knew it was going to be a bad print with onl	Negative

64720 rows × 2 columns

```
In [67]:
              dict neg pos = {}
              for index, value in lex neg[0].items():
            2
            3
                  dict neg pos[value] = "negative"
            4
              for index, value in lex pos[0].items():
                  dict_neg_pos[value] = "positive"
In [216]:
            1
              import re
              def tokenizer(theText):
            2
            3
                  the Tokens = re.findall(r'\b\w[\w-]*\b', the Text.lower())
            4
                  return theTokens
            5
              reviews tokenized = []
              reviews = All data['Reviews']
            7
           8
              for index, value in reviews.items():
           9
           10
                  reviews tokenized.append(tokenizer(value))
              All_data['Reviews_Tokenized'] = reviews_tokenized
           11
           12
```

Part A: Sentiment lexicon-based classifier.

Sentiment lexicon-based classifier. Create a classifier using a sentiment lexicon. A lexicon from Hu and Liu [1] is provided in the directory opinion lexicon English, but you are welcome to find and use (with attribution, of course) another. Tokenize the data, and classify each document as positive if and only if it has more positive sentiment words than negative sentiment words. Compute and report the accuracy and F1 score (on detecting positive reviews) on the test set, using this lexicon-based classifier.

```
In [210]:
            1
              def result of sentiment analysis(review):
            2
                   pos count = 0
            3
                   neg count = 0
            4
                   for token in review:
            5
                       if token in dict neg pos:
                           s = dict neg pos.get(token)
            6
            7
                           if s == "positive":
            8
                               pos count = pos count + 1
            9
                           else:
           10
                               neg count = neg count + 1
           11
                   if pos count >= neg count:
           12
                       return "Positive"
           13
                   else:
                       return "Negative"
           14
           15
              sentiments_y = []
           16
           17
              reviews tokens = Testset data['Reviews Tokenized']
               for review in reviews tokens:
           18
           19
                   sentiments y.append(result of sentiment analysis(review))
```

```
In [211]: 1 Testset_data['Sentiments_Y'] = sentiments_y
2 Testset_data
```

Out[211]:

	Reviews	Sentiments	Reviews_Tokenized	Sentiments_Y
54756	you're so	Negative	[you, re, so]	Positive
43964	no one would deny that spillane's writing has	Negative	[no, one, would, deny, that, spillane, s, writ	Negative
21339	i can ? t recall seeing a film recently that w	Positive	[i, can, t, recall, seeing, a, film, recently,	Positive
56309	the times are changing , though , and the gear	Positive	[the, times, are, changing, though, and, the,	Positive
54493	i certainly wish that was a new trend in holly	Negative	[i, certainly, wish, that, was, a, new, trend,	Positive
	•••			
9945	details essential to the story are so improbab	Negative	[details, essential, to, the, story, are, so,	Negative
62137	as many great movies that got cult status thro	Positive	[as, many, great, movies, that, got, cult, sta	Positive
10376	if we encourage terrorism abroad (from bening	Positive	[if, we, encourage, terrorism, abroad, from, b	Negative
50983	alas , the times are a-changin' .	Positive	[alas, the, times, are, a-changin]	Positive
6022	the chase is also shot and edited in that " je	Positive	[the, chase, is, also, shot, and, edited, in,	Positive

400 rows × 4 columns

Accuracy and F1 Score calculation

```
In [72]: 1     actual = Testset_data['Sentiments']
2     predicted = Testset_data['Sentiments_Y']
3
4     tp = np.sum((actual=='Positive') & (predicted=='Positive'))
5     fp = np.sum((actual!='Positive') & (predicted=='Positive'))
6     tn = np.sum((actual=='Negative') & (predicted=='Negative'))
7     fn = np.sum((actual!='Negative') & (predicted=='Negative'))
8
9     accuracy = (tp+tn)/(tp+tn+fp+fn)
10     precision = tp/(tp+fp)
11     recall = tp/(tp+fn)
12     f1 = 2 * (precision * recall) / (precision + recall)
In [73]: 1     print (accuracy, precision, recall, f1)
```

0.5375 0.4854014598540146 0.751412429378531 0.5898004434589801

Part B: Logistic regression classifier.

Out[367]: 3654

Train a (binary) logistic regression classifier on your training set using features of your own choosing, and report its accuracy and F1 score (as above) on the test set. In your write-up, describe the features you have chose and explain the reasoning behind your choice. Do not use pretrained word vectors or any features implemented or constructed by anyone else. Do not use an existing implementation of logistic regression, stochastic gradient descent, or automatic differentiation.

```
In [364]: 1 Training_data = All_data.copy()
2 Testset_data = All_data.sample(n=4000, random_state=1)
3 Training_data.drop(Testset_data.index)
4 Training_data = Training_data.sample(n=20000, random_state=1)
```

Bag of word Model

```
In [365]:
            1
              word_dict = {}
            2
            3
              def add_all_workds_to_dict(words):
                   for word in words:
            4
            5
                       if word in word dict:
                           word dict[word] = word dict.get(word) + 1
            6
            7
                       else:
                           word_dict[word] = 1
            8
            9
               for words in Training data["Reviews Tokenized"]:
           10
           11
                   add all workds to dict(words)
In [366]:
            1
               frequent word set = set()
            2
               for key, value in word dict.items():
            3
                   if value > 10:
                       frequent word set.add(key)
            4
In [367]:
            1 len(frequent word set)
```

```
In [368]: 1 Training_data
```

Out[368]:

	Reviews	Sentiments	Reviews_Tokenized
54756	you're so	Negative	[you, re, so]
43964	no one would deny that spillane's writing has	Negative	[no, one, would, deny, that, spillane, s, writ
21339	i can? t recall seeing a film recently that w	Positive	[i, can, t, recall, seeing, a, film, recently,
56309	the times are changing , though , and the gear	Positive	[the, times, are, changing, though, and, the,
54493	i certainly wish that was a new trend in holly	Negative	[i, certainly, wish, that, was, a, new, trend,
44239	in pay it forward leder continues in this vein	Negative	[in, pay, it, forward, leder, continues, in, t
29593	the humor especially works well in this case ,	Positive	[the, humor, especially, works, well, in, this
22651	here's a film that actually gives away most of	Positive	[here, s, a, film, that, actually, gives, away
7397	a bad guy that's not really bad .	Positive	[a, bad, guy, that, s, not, really, bad]
10320	this vacuous picture throws in a standard down	Negative	[this, vacuous, picture, throws, in, a, standa

20000 rows × 3 columns

5

```
In [369]:
              Training_data_with_features = pd.DataFrame(columns = frequent_word_set)
              for review in Training_data["Reviews_Tokenized"]:
                  i = len(Training data with features)
                  Training data with features.loc[i] = 0
                  for word in review:
            5
            6
                      if word in frequent word set:
            7
                          count = Training data with features.loc[i, word]
            8
                          Training_data_with_features.loc[i, word] = count + 1
              train X = Training data with features.astype(float)
              train_Y = []
In [370]:
              for sentiment in Training_data["Sentiments"]:
            2
            3
                  if sentiment == "Positive":
            4
                      train_Y.append(1)
```

Logistic Regression Model Classifier

train_Y.append(0)

else:

In [372]:

```
In [371]:
            1
              class Logistic Regression() :
                  def __init__(self, learning_rate=0.001, n_iters=1000):
            2
            3
                       self.lr = learning rate
            4
                       self.n_iters = n_iters
            5
                       self.weights = None
            6
                       self.bias = None
            7
                  def fit(self, X, y):
            8
            9
                       n samples, n_features = X.shape
           10
                       self.weights = np.zeros(n_features)
           11
                       self.bias = 0
           12
           13
                       for i in range(self.n_iters):
           14
                           model linear = np.dot(X, self.weights) + self.bias
           15
                           predict y = self._sigmoid(model_linear)
           16
                           dw = (1 / n_samples) * np.dot(X.T, (predict_y - y))
                           db = (1 / n_samples) * np.sum(predict_y - y)
           17
                           self.weights -= self.lr * dw
           18
           19
                           self.bias -= self.lr * db
           20
           21
                  def predict(self, X):
           22
                       model_linear = np.dot(X, self.weights) + self.bias
           23
                       predict y = self._sigmoid(model_linear)
                       predict_y_cls = [1 if i > 0.5 else 0 for i in predict y]
           24
           25
                       return np.array(predict_y_cls)
           26
           27
                  def sigmoid(self, x):
           28
                       return 1 / (1 + np.exp(-x))
```

```
regression.fit(train X, train Y)
              Testset data with features = pd.DataFrame(columns = frequent word set)
In [373]:
            1
            2
              for review in Testset data["Reviews Tokenized"]:
            3
                   i = len(Testset data with features)
                  Testset data with features.loc[i] = 0
            4
                   for word in review:
            5
                       if word in frequent word set:
            6
            7
                           count = Testset data with features.loc[i, word]
                           Testset data with features.loc[i, word] = count + 1
            8
            9 test X = Testset data with features.astype(float)
In [374]:
            1
              test Y = []
              for sentiment in Testset data["Sentiments"]:
            2
                   if sentiment == "Positive":
            3
```

regression = Logistic Regression()

test Y.append(1)

test Y.append(0)

```
In [375]: 1 predictions = regression.predict(test_X)
2 type(predictions)
```

Out[375]: numpy.ndarray

4

5

6

else:

```
In [376]: 1 actual = np.array(test_Y)
2 predicted = predictions
3
4 tp = np.sum((actual==1) & (predicted==1))
5 fp = np.sum((actual!=1) & (predicted==1))
6 tn = np.sum((actual==0) & (predicted==0))
7 fn = np.sum((actual!=0) & (predicted==0))
8
9 accuracy = (tp+tn)/(tp+tn+fp+fn)
10 precision = tp/(tp+fp)
11 recall = tp/(tp+fn)
12 f1 = 2 * (precision * recall) / (precision + recall)
In [377]: 1 print (accuracy, precision, recall, f1)
```

0.53325 0.5237562884292901 0.9199803632793323 0.6674977738201247

Breaking good.

Case 1: Positive by human English speakers, and your lexicon classifier predicts it as positive, whereas your logistic regression classifier predicts it as negative.

```
In [340]:
              text1 = tokenizer("I've recently noticed something I had not even consi
             result of sentiment analysis(text1)
Out[340]: 'Positive'
In [341]:
             breaking bad text = text1
           2 breaking bad text with features = pd.DataFrame(columns = frequent word
             breaking bad text with features.loc[0] = 0
              for word in breaking bad text:
           5
                  if word in frequent word set:
                      count = breaking bad text with features.loc[0, word]
           6
           7
                      breaking bad text with features.loc[0, word] = count + 1
             breaking bad text X = breaking bad text with features.astype(float)
             regression.predict(breaking bad text X) # 0 means negative and 1 means
Out[341]: array([0])
```

Case 2: Human positive and your lexicon classifier predicts it as negative, whereas your logistic regression classifier predicts it as positive.

```
In [380]: 1 text2 = tokenizer("You can bet that anybody who has ever seen Karan's m
2 result_of_sentiment_analysis(text2)
Out[380]: 'Negative'
```

```
In [381]:
              breaking bad text = text2
              breaking bad text with features = pd.DataFrame(columns = frequent word
           2
              breaking_bad_text_with_features.loc[0] = 0
              for word in breaking bad text:
           5
                  if word in frequent word set:
                      count = breaking_bad_text_with_features.loc[0, word]
           7
                      breaking bad text with features.loc[0, word] = count + 1
              breaking bad text X = breaking bad text with features.astype(float)
           9
              regression.predict(breaking_bad_text_X) # 0 means negative and 1 means
           10
Out[381]: array([1])
```

Case 3: Both of your classifiers predict it as negative.

```
text3 = tokenizer("They're all unhappy or marginally so about noodles i
In [409]:
              result_of_sentiment_analysis(text3)
Out[409]: 'Negative'
In [410]:
              breaking bad text = text3
              breaking bad text with features = pd.DataFrame(columns = frequent word
              breaking bad text with features.loc[0] = 0
              for word in breaking bad text:
            5
                  if word in frequent word set:
                      count = breaking bad text with features.loc[0, word]
            6
            7
                      breaking_bad_text_with_features.loc[0, word] = count + 1
              breaking bad text X = breaking bad text with features.astype(float)
            9
              regression.predict(breaking bad text X) # 0 means negative and 1 means
           10
Out[410]: array([0])
  In [ ]:
```