a2-Word2Vec-and-gloVe-embeddings-dan-jang

October 25, 2023

1 CS410: Natural Language Processing, Fall 2023

1.1 A2: `Word2Vec` and GloVe Embeddings, Dan Jang - 10/23/2023

Description of Assignment

Introduction Using the same training & testing datasets from our first assignment, *A1: Sentiment Analysis Text Classification*, in this second assignment - *A2: `Word2Vec` and `GloVe` Embeddings*, we will specifically focus on the experimentation of two specific pretrained models: `word2vec-google-news-300` and `glove-wiki-gigaword-300`, which will be downloaded via the gensim library.

Specifically, while both the *A1* (previous) & *A2* (current) assignments each implement a text-classification model that predicts sentiment & the same training/testing datasets, in *this assignment*, *A2: `Word2Vec` and GloVe Embeddings*, we will use **pretrained embeddings** from the `Word2Vec` and `GloVe` **models** (*instead of feature-engineering* as from our previous *A1* assignment).

Data Preparation Almost the same from our last assignment, *A1: Sentiment Analysis Text Classification*, we will use a pair of training & testing datasets containing product customer reviews, which is named the "Multilingual Amazon Reviews Corpus", in a `.json` container format, with several columns. The assignment will focus on a smaller subset of the original dataset, where we will focus on **two (2) columns**: 1. "review_title" - self-explanatory 2. "stars" - an integer, either 1 or 5, where the former indicates "negative" and 5 indicates "positive."

There will be a training set & a test set.

We will load the dataset using Python & use respective libraries to implement our text-classification model.

Optionally, we will preprocess the data if needed, e.g. case-formating - where in this second assignment, *A2: `Word2Vec` and GloVe Embeddings*, the instructions state that more effective preprocessing can be achieved if matches such preprocessing that was applied to the aforementioned pretrained models, `word2vec-google-news-300` and `glove-wiki-gigaword-300`.

Pretrained Models Through the gensim library, we will experiment with the `word2vec-google-news-300` and `glove-wiki-gigaword-300` **pretrained models**, focusing on these aspects: 1. **Comparison** of the two pretrained models. 2. **Visualization**, using tools such as t-SNE for embedding-dimensionality reduction, to visualize & discuss the following related results: I. "**emotion words**", e.g. 'happy', 'love', etc., in observing how these emotion words are "*positioned in the vector space.*" II. "**gender and occupation**", e.g., 'woman', 'queen', 'neuroscientist', etc., to "*explore biases and stereotypes in embeddings.*"

Text Classification Model To build our text-classification model, we will **follow these steps**: 1. Any ***one*** chosen suitable algorithm for text classification. 2. Creating *word representations* of the text data (conversion of text for numerical features). 3. Training of the text-classification model using the training dataset, "sentiment_train.json." 4. Evaluation of our text-classification model using the testing dataset, "sentiment_test.json."

Results & Analysis A detailed analysis of the model's performance by comparing the results from the output of our two algorithms, where we will **include the following**: 1. *F1-score* or other relevant metrics. 2. Any challenges or limitations of the text-classification model/task.

Requirements

1.1.1 Libraries & Constants Initialization

[23]:
```python
### 0.) Libraries
#from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import classification_report
from sklearn.manifold import TSNE
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
#from nltk.sentiment.vader import SentimentIntensityAnalyzer
import json
import pandas
import numpy as np
import matplotlib.pyplot as plot
import gensim.downloader

# Loading the pretrained models for le embeddings, using the gensim library!
print("Downloading / Loading the Word2Vec pretrained model through the gensim␣
 ↪library...")
wordyvec = gensim.downloader.load('word2vec-google-news-300')
print("...the Word2Vec model has been downloaded / loaded!")

print("Downloading / Loading the GloVe pretrained model through the gensim␣
 ↪library...")
glove = gensim.downloader.load('glove-wiki-gigaword-300')
```

```
print("...the GloVe model has been downloaded / loaded!")

print()
print("Downloading NLTK punkt, stopwords, & wordnet...")
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
print()
print("...done!")
```

```
Downloading / Loading the Word2Vec pretrained model through the gensim
library…
…the Word2Vec model has been downloaded / loaded!
Downloading / Loading the GloVe pretrained model through the gensim library…
…the GloVe model has been downloaded / loaded!

Downloading NLTK punkt, stopwords, & wordnet…
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\Dan\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Dan\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\Dan\AppData\Roaming\nltk_data…
```

```
…done!
```

1.1.2 t-SNE Visualization of the Word2Vec & GloVe Pretrained Model Embeddings

[24]:

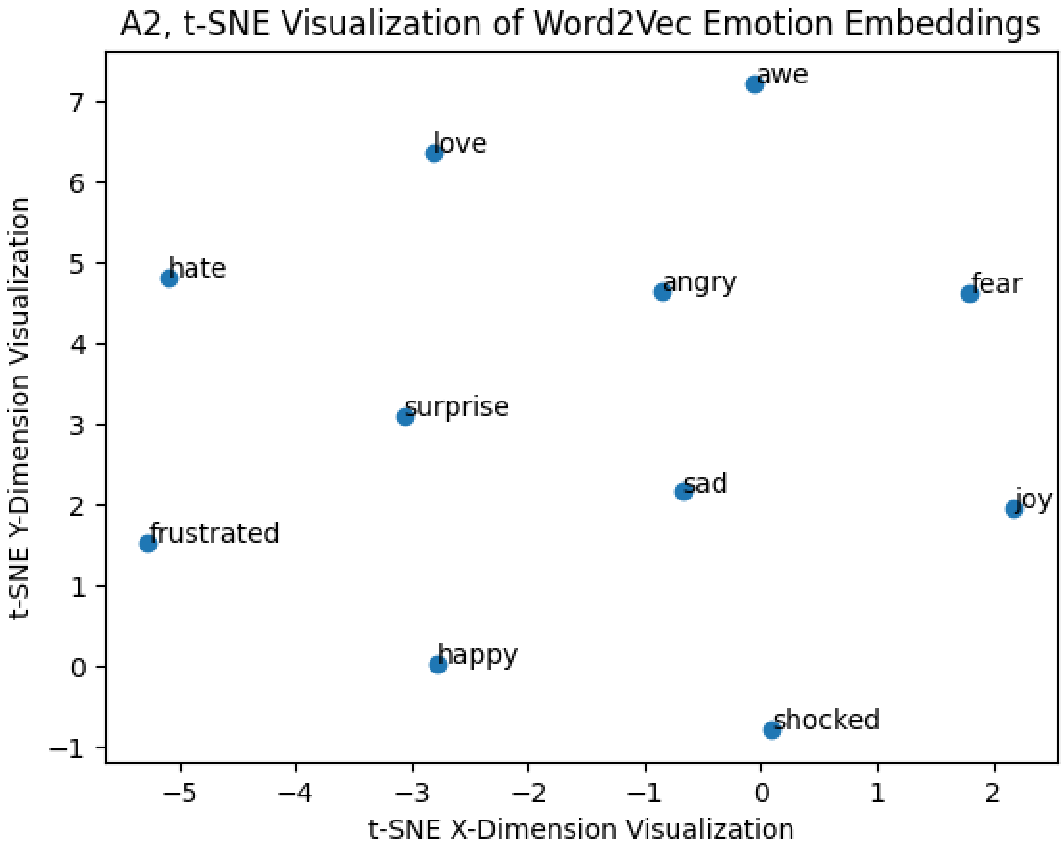
```
##### CS410: Natural Language Processing, Fall 2023 - 10/23/2023
##### A2: Word2Vec and GloVe Embeddings, Dan Jang - tSNE Visualization␣
↪Implementation
#### Objective: Exploring Natural Language Processing (NLP), by building a␣
↪text-classifier
#### for a text classification task, predicting whether a piece of text is␣
↪"positive" or "negative."
#### ...with the inclusion of two (2) pretrained models, Word2Vec and GloVe,␣
↪for word embeddings.

## For converting accuracy to percent
percentness = float(100)

## 1.0.) Constants, Variables, & Datasets

# trainfile = str(trainfile)
```

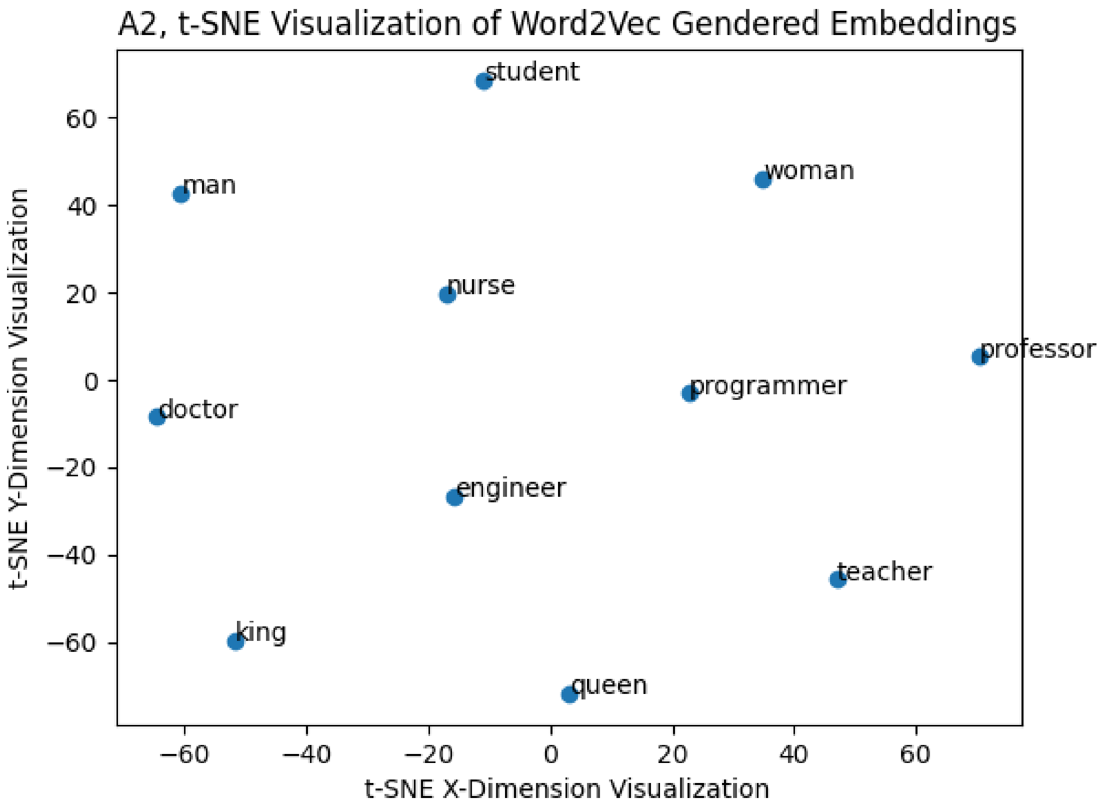
```
# testfile = str(testfile)
traindata = []
testdata = []

# 1.0.2.) Embedding Functions
def wordyvec_embedder(words):
    return np.array([wordyvec[word] for word in words])# if w in wordyvec else␣
 ↪np.zeros(300))

def glove_embedder(words):
    return np.array([glove[word] for word in words])# if w in glove else np.
 ↪zeros(300))
# def wordyvec_embedder(words, wordyvec=wordyvec):
#     beds = []
#     for w in words:
#         if w in wordyvec:
#             beds.append(wordyvec[w])
#         else:
#             beds.append(np.zeros(300))
#     return np.array(beds)
#     #return np.array([wordyvec[word] for word in wordlist])# if w in wordyvec␣
 ↪else np.zeros(300))

# def glove_embedder(wordlist, glove=glove):
#     beds = []
#     for w in wordlist:
#         if w in glove:
#             beds.append(glove[w])
#         else:
#             beds.append(np.zeros(300))
#     return np.array(beds)
#     #return np.array([glove[word] for word in wordlist])# if w in glove else␣
 ↪np.zeros(300))

def plotter(beds, wordlist, name):
    plot.scatter(beds[:,0], beds[:,1])
    plot.title(name)
    plot.xlabel('t-SNE X-Dimension Visualization')
    plot.ylabel('t-SNE Y-Dimension Visualization')
    for idx, w in enumerate(wordlist):
        plot.annotate(w, (beds[idx,0], beds[idx,1]))
    plot.show()


### Sanity Debug Data Check Function [Update: Fixed via dependency upgrade for␣
 ↪threadpoolctl==3.1.0 or above, as credited below]
```

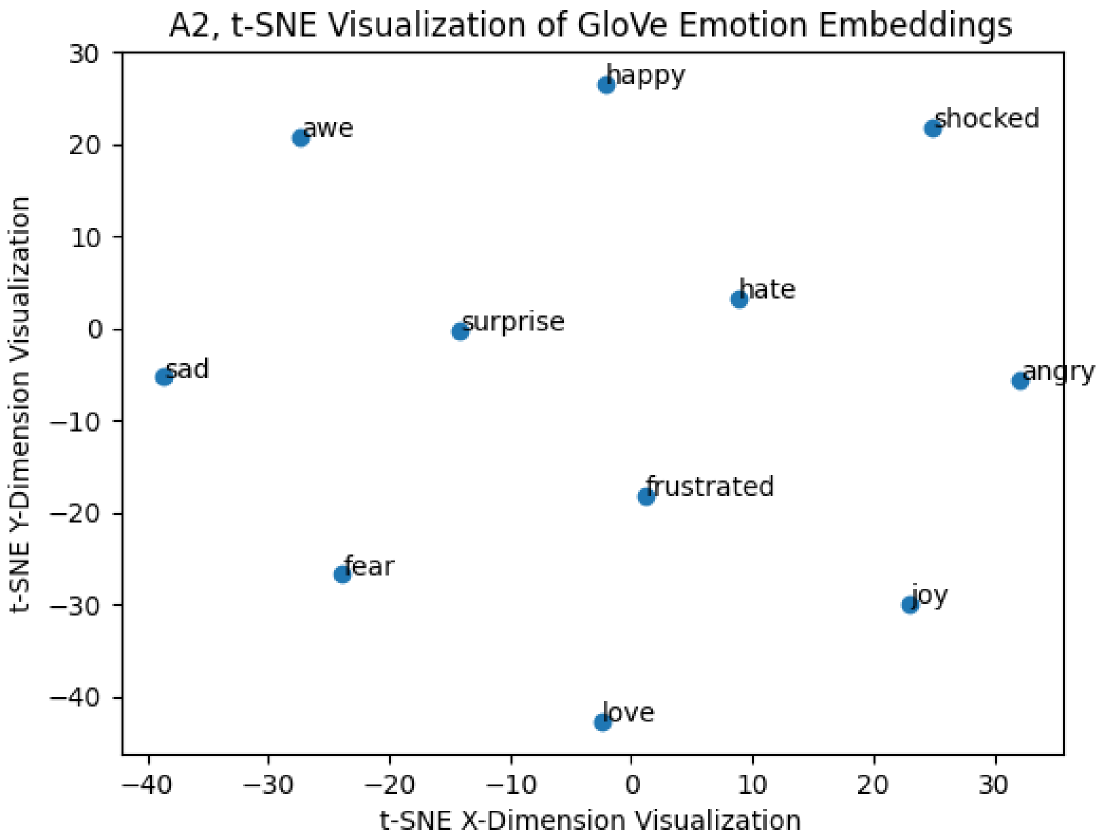
```
#### Super Special Credits to: https://stackoverflow.com/questions/73283082/
↪t-sne-sklearn-attributeerror-nonetype-object-has-no-attribute-split
#### For saving me from hours of frustration & rewriting my code over and over
def verify_model(wordlist, model):
    missingwords = [w for w in wordlist if w not in model]
    if missingwords:
        print('The following words are missing from the model: {}'.
↪format(missingwords))
    else:
        print('All words are present in the model!')

## 1.0.2.1.) Plotting the Word2Vec & GloVe Embeddings for Emotion & Gendered␣
↪Words as t-SNE Visualizations!
def visualization():

    ## 1.0.1.) List of emotion & gendered words for use with tSNE visualization␣
↪of embeddings
    emotion = ['happy', 'sad', 'angry', 'joy', 'love', 'fear', 'surprise',␣
↪'awe', 'frustrated', 'shocked', 'hate']
    gendered = ['woman', 'man', 'queen', 'king', 'doctor', 'nurse', 'engineer',␣
↪'professor', 'teacher', 'programmer', 'student']

    visualizer = TSNE(n_components=2, random_state=0, perplexity=10)

    ### Sanity Debug Check
    verify_model(emotion, wordyvec)
    verify_model(gendered, wordyvec)
    verify_model(emotion, glove)
    verify_model(gendered, glove)

    wordyvec_emotionization = visualizer.
↪fit_transform(wordyvec_embedder(emotion))
    wordyvec_genderization = visualizer.
↪fit_transform(wordyvec_embedder(gendered))

    glove_emotionization = visualizer.fit_transform(glove_embedder(emotion))
    glove_genderization = visualizer.fit_transform(glove_embedder(gendered))
    plotter(wordyvec_emotionization, emotion, 'A2, t-SNE Visualization of␣
↪Word2Vec Emotion Embeddings')
    plotter(wordyvec_genderization, gendered, 'A2, t-SNE Visualization of␣
↪Word2Vec Gendered Embeddings')
    plotter(glove_emotionization, emotion, 'A2, t-SNE Visualization of GloVe␣
↪Emotion Embeddings')
    plotter(glove_genderization, gendered, 'A2, t-SNE Visualization of GloVe␣
↪Gendered Embeddings')
```

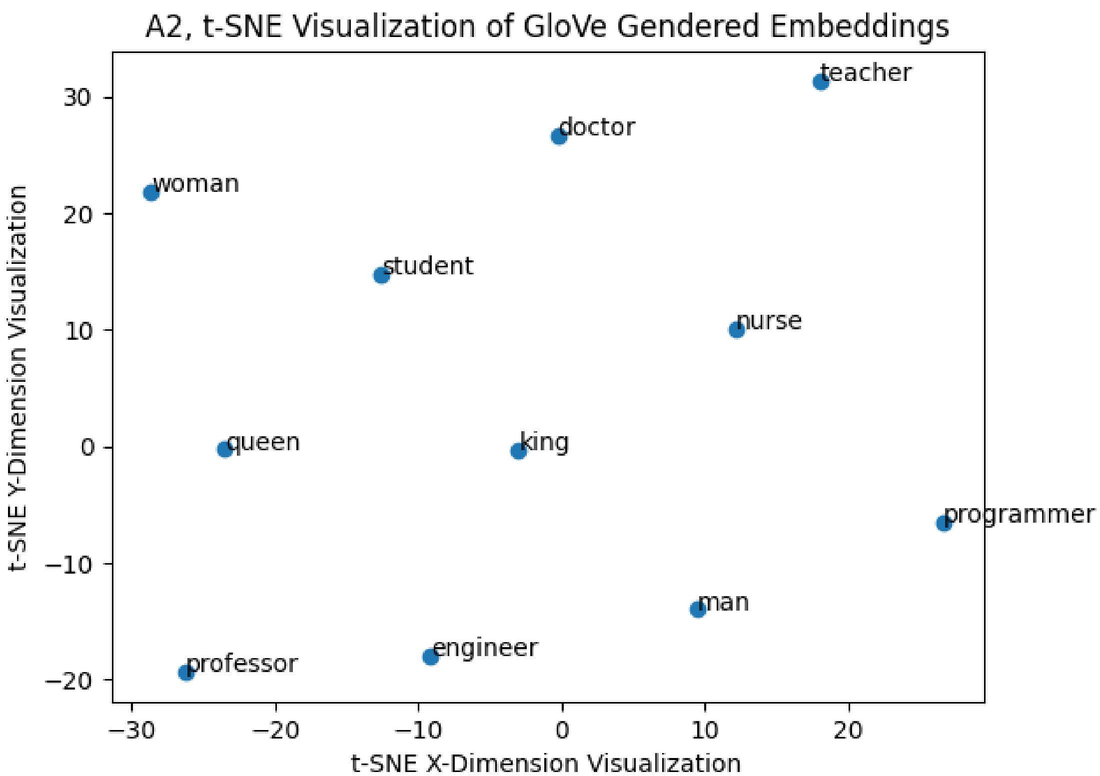
```
visualization()
```

```
All words are present in the model!
All words are present in the model!
All words are present in the model!
All words are present in the model!
```




A2, t-SNE Visualization of Word2Vec Gendered Embeddings
student
man
woman
nurse
professor
programmer
doctor
engineer
teacher
king
queen
60
40
20
0
−20
−40
−60
60
40
20
0
−20
−40
−60
t-SNE X-Dimension Visualization
t-SNE Y-Dimension Visualization


A2, t-SNE Visualization of GloVe Emotion Embeddings
t-SNE Y-Dimension Visualization
t-SNE X-Dimension Visualization
30
20
10
0
−10
−20
−30
−40
−40
−30
−20
−10
0
10
20
30
happy
awe
shocked
hate
surprise
sad
angry
frustrated
fear
joy
love



1.1.3 Main Implementation: *Text Classification /w Embeddings from Two (2) Pre-trained Models*, `word2vec-google-news-300` and `glove-wiki-gigaword-300`.

[26]:
```
##### CS410: Natural Language Processing, Fall 2023 - 10/23/2023
##### A2: Word2Vec and GloVe Embeddings, Dan Jang - Main Implementation
#### Objective: Exploring Natural Language Processing (NLP), by building a␣
↪text-classifier
#### for a text classification task, predicting whether a piece of text is␣
↪"positive" or "negative."
#### ...with the inclusion of two (2) pretrained models, Word2Vec and GloVe,␣
↪for word embeddings.

### 1.1.a) Logistic Regression algorithm using sklearn.linear_model.
↪LogisticRegression
### https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.
↪LogisticRegression.html
### Returns four (4) thingys:
# I.) accuracy_score,
# II.) f1_score,
# III.) confusion_matrix,
# & IV.) classification_report.
```

```python
def algo_two(xtrain, ytrain, xtest, ytest):
    lreg = LogisticRegression()

    lreg.fit(xtrain, ytrain)
    predictionresults = lreg.predict(xtest)

    return accuracy_score(ytest, predictionresults), f1_score(ytest,␣
 ↪predictionresults), confusion_matrix(ytest, predictionresults),␣
 ↪classification_report(ytest, predictionresults)

# ### 1.2.) NLTK Vader Lexicon-based Sentiment Analysis Classifier
# ### https://www.nltk.org/_modules/nltk/sentiment/vader.html
# ## sith_holocron = le sentiment intensity analyzer from NLTK
# ## theforce = le sentiment score
# ## aura = le text that is to be analyzed by [darth]vader from NLTK
# def darth(aura):
#     sith_holocron = SentimentIntensityAnalyzer()
#     theforce = sith_holocron.polarity_scores(aura)
#     # Debug Statement #2
#     #print(theforce['compound'])
#     return theforce['compound']

### A2-Specific: Helper functions for implementing the two pretrained models,␣
 ↪Word2Vec & GloVe, for word embeddings.
def avgwordvec(words, model):
    wordlist = words.split()
    vecs = [model[w] for w in wordlist if w in model]
    if vecs:
        return sum(vecs) / len(vecs)
    else:
        return [0] * model.vector_size

def text2vectorizer(words, model):
    beds = [avgwordvec(w, model) for w in words]
    return beds

### A2-Specific: Preprocessing function for the text-reviews in the datasets␣
 ↪using NLTK Tokenization, Stopwords & Lemmatization
def preprocess(txt):

    # Tokenization
    #print("Tokenizing the text-reviews in the datasets...")
    tokenz = word_tokenize(txt)
    #print("...Tokenization is complete!")

    # Stopwords
```

```
    #print("Removing stopwords from the tokenized text-reviews in the datasets..
↪.")
    stoppedwords = set(stopwords.words('english'))
    filteredwordsthatwerestopped = [w for w in tokenz if w.lower() not in␣
↪stoppedwords]
    #print("...Stopwords have been removed!")

    # Lemmatization
    #print("Lemmatizing the text-reviews in the datasets...")
    lemmatization = WordNetLemmatizer()
    lemmatizedtokenz = [lemmatization.lemmatize(w) for w in␣
↪filteredwordsthatwerestopped]
    #print("...Lemmatization is complete!")

    return ' '.join(lemmatizedtokenz)

def main(): #trainfile, testfile):
    print("Welcome, this is the main program for A2: Word2Vec and GloVe␣
↪Embeddings.")
    print("Written by Dan J. for CS410: Natural Language Processing, Fall 2023.
↪")
    print("\nWe will use one (1) classification algorithm:\n& 1. Logistic␣
↪Regression + two (2) pretrained models for embeddings, Word2Vec & GloVe.\n...
↪to create a text-classifier to guess negative or positive sentimentiality␣
↪based on various text-reviews of products.")

    # # Loading the pretrained models for le embeddings, using the gensim␣
↪library!
    # glove = gensim.downloader.load('glove-wiki-gigaword-300')
    # wordyvec = gensim.downloader.load('word2vec-google-news-300')

    # ## For converting accuracy to percent
    # percentness = float(100)

    # ## 1.0.) Constants, Variables, & Datasets

    # # trainfile = str(trainfile)
    # # testfile = str(testfile)
    # traindata = []
    # testdata = []

    # ## 1.0.1.) List of emotion & gendered words for use with tSNE␣
↪visualization of embeddings
    # emotion = ['happy', 'sad', 'angry', 'joy', 'love', 'fear', 'surprise',␣
↪'awe', 'frustrated', 'shocked']
```

```python
    # gendered = ['woman', 'man', 'queen', 'king', 'doctor', 'nurse',␣
↪'engineer', 'professor', 'teacher', 'technician', 'programmer']

    # 1.0.I.A) Debug Statements #1a for dataset loading times:
    print("\nLoading the training & testing datasets...")
    # with open(trainfile, "r") as trainfile:
    with open("sentiment_train.json", "r") as trainfile:
        #traindata = json.load(trainfile)
        for row in trainfile:
            traindata.append(json.loads(row))

    trainframe = pandas.DataFrame(traindata)

    # with open(testfile, "r") as testfile:
    with open("sentiment_test.json", "r") as testfile:
        #testdata = json.load(testfile)
        for row in testfile:
            testdata.append(json.loads(row))

    testframe = pandas.DataFrame(testdata)

    # 1.0.I.B) Debug Statements #1b for dataset loading times:
    print("Successfully loaded the training & testing datasets!\n")

    ## 1.0.1.) Initial Preprocessing of the training & testing data
    ## First, we isolate our two (2) columns, "review_title" & "stars."
    ## Second, we will convert values in the "stars" column so that 1␣
↪[negative] = 0 & 5 [positive] = 1.
    ## This will allow us to make the negative or positive sentiment a binary␣
↪value-based thingy.
    trainframe = trainframe[['review_title', 'stars']]
    trainframe['stars'] = trainframe['stars'].apply(lambda x: 1 if x == 5 else␣
↪0)

    testframe = testframe[['review_title', 'stars']]
    testframe['stars'] = testframe['stars'].apply(lambda x: 1 if x == 5 else 0)


    ## 1.1.) A2-Specific Further Preprocessing of Data using NLTK Tokenization,␣
↪Stopwords & Lemmatization

    print("Starting preprocessing of the training dataset...")
    trainframe['review_title'] = trainframe['review_title'].apply(preprocess)
    print("...Preprocessing of the training dataset is complete!")

    print("Starting preprocessing of the testing dataset...")
    testframe['review_title'] = testframe['review_title'].apply(preprocess)
```

```
    print("...Preprocessing of the testing dataset is complete!")

    # A2-Specific: 1.0.1.) Applying Word2Vec & GloVe Embeddings to vectorized␣
↪data
    x2train = trainframe['review_title']
    x2test = testframe['review_title']

    print("Processing the training & testing datasets for Word2Vec...")
    x2train1 = text2vectorizer(x2train, wordyvec)
    x2test1 = text2vectorizer(x2test, wordyvec)
    print("Word2Vec has been applied to the training & testing datasets!")

    print("Processing the training & testing datasets for GloVe...")
    x2train2 = text2vectorizer(x2train, glove)
    x2test2 = text2vectorizer(x2test, glove)
    print("GloVe has been applied to the training & testing datasets!")

    ## Note: Below would have needed 31.9 GB of allocated RAM to run, which␣
↪would crash my computer / take big bucks in Google Colab, heh.
    # # A2-Specific: 1.0.1.2.) Preprocessing Data for Word2Vec & GloVe␣
↪Embeddings
    # print("Creating combined datasets to preprocess both Word2Vec & GloVe␣
↪embeddings for the training & testing datasets...")
    # x2train2full = [list(a) + list(b) for a, b in zip(x2train1, x2train2)]
    # x2test2full = [list(a) + list(b) for a, b in zip(x2test1, x2train2)]
    # print("Combined datasets have been created!")

    # ## 1.0.1.) Applying NLTK Vader Sentiment
    # ## https://www.nltk.org/_modules/nltk/sentiment/vader.html
    # x2train = trainframe
    # x2train = x2train[['review_title', 'stars']]
    # # Have to truncate the training dataset so that it does not crash my␣
↪computer, heh.
    # # Using a random_state seed of 2005, which was when Star Wars III was␣
↪released (when Vader was technically introduced in the prequelz).
    # #x2train = x2train.sample(n=20000, random_state=2005)
    # print("Now applying NLTK Vader sentiment analysis to the training dataset.
↪..")
    # x2train['nltk_vader_sentiment'] = x2train['review_title'].apply(darth)
    # print("...Vader has been applied to the training set.")
    y2train = trainframe['stars']

    # x2test = testframe
    # x2test = x2test[['review_title', 'stars']]
    # print("Now applying NLTK Vader sentiment analysis to the testing dataset..
↪.")
```

```
    # x2test['nltk_vader_sentiment'] = x2test['review_title'].apply(darth)
    # print("...Vader has been applied to the testing set.")

    # ## 1.1.) Vectorization of the text-reviews in the datasets using sklearn.
↪feature_extraction.text.CountVectorizer.
    # ## As a core component of text-classification, the vectorization process␣
↪of the text-review data is essential for feature engineering in natural␣
↪language processing.
    # ## https://scikit-learn.org/stable/modules/generated/sklearn.
↪feature_extraction.text.CountVectorizer.html
    # vectorization_machine_9000 = CountVectorizer()
    # xtrain = vectorization_machine_9000.
↪fit_transform(trainframe['review_title'])
    # xtrain = xtrain.toarray()
    # ytrain = trainframe['stars']

    # xtest = vectorization_machine_9000.transform(testframe['review_title'])
    # xtest = xtest.toarray()


    ytest = testframe['stars']

    # ## 1.1.1.) Applying NLTK Vader Sentiment to vectorized data
    # x2traintext = vectorization_machine_9000.
↪fit_transform(x2train['review_title'])
    # x2trainsentiment = x2train['nltk_vader_sentiment'].values.reshape(-1,1)
    # parsed_x2traintext = pandas.DataFrame(x2traintext.toarray())
    # parsed_x2trainsentiment = pandas.DataFrame(x2trainsentiment)

    # x2testtext = vectorization_machine_9000.transform(x2test['review_title'])
    # x2testsentiment = x2test['nltk_vader_sentiment'].values.reshape(-1,1)
    # parsed_x2testtext = pandas.DataFrame(x2testtext.toarray())
    # parsed_x2testsentiment = pandas.DataFrame(x2testsentiment)

    # x2train = pandas.concat([parsed_x2traintext, parsed_x2trainsentiment],␣
↪axis=1)
    # x2test = pandas.concat([parsed_x2testtext, parsed_x2testsentiment],␣
↪axis=1)


    ### 1.0.2b) Run Text-Classification Algorithms & Print the Model Results -␣
↪with NLTK Vader sentiment analysis (& vectorization)
    print("-----\n")
    print("Running algorithm on le training & testing datasets (with pretrained␣
↪model embeddings)...")
```

```
    print("Running Logistic Regression algorithm, version A (Word2Vec)...")
    bed1accuracy, bed1f1, bed1cmatrix, bed1creport = algo_two(x2train1, y2train, x2test1, ytest)
    print("..First embeddings are done!")

    print("Running Logistic Regression algorithm, version B (GloVe)...")
    bed2accuracy, bed2f1, bed2cmatrix, bed2creport = algo_two(x2train2, y2train, x2test2, ytest)
    print("..First embeddings are done!")

    print("...All Done!")
    print("-----\n")

    print("Here are le results [Logistic Regression /w two (2) pretrained model-based embedding classification]...\n")
    print("Logistic Regression Algorithm, Version A: Word2Vec Pretrained Model-based Embeddings Performance, Metrics, & Results:")
    print("...Accuracy was found to be, ", bed1accuracy * percentness, "%,")
    print("...F1 Score was found to be: ", bed1f1, ",")
    print("...with a Confusion Matrix: \n", bed1cmatrix, ",")
    print("...& lastly, the classification Report: \n", bed1creport)
    print("-----\n")

    print("Logistic Regression Algorithm, Version B: GloVe Pretrained Model-based Embeddings Performance, Metrics, & Results:")
    print("...Accuracy was found to be, ", bed2accuracy * percentness, "%,")
    print("...F1 Score was found to be: ", bed2f1, ",")
    print("...with a Confusion Matrix: \n", bed2cmatrix, ",")
    print("...& lastly, the classification Report: \n", bed2creport)
    print("-----\n")

#a1_program = a1_text_classifer("sentiment_train.json", "sentiment_test.json")

#### Commented out codez
# def main():

if __name__ == "__main__":
    main()
```

Welcome, this is the main program for A2: Word2Vec and GloVe Embeddings.
Written by Dan J. for CS410: Natural Language Processing, Fall 2023.

We will use one (1) classification algorithm:
& 1. Logistic Regression + two (2) pretrained models for embeddings, Word2Vec & GloVe.
…to create a text-classifier to guess negative or positive sentimentiality

```
based on various text-reviews of products.

Loading the training & testing datasets…
Successfully loaded the training & testing datasets!

Starting preprocessing of the training dataset…
…Preprocessing of the training dataset is complete!
Starting preprocessing of the testing dataset…
…Preprocessing of the testing dataset is complete!
Processing the training & testing datasets for Word2Vec…
Word2Vec has been applied to the training & testing datasets!
Processing the training & testing datasets for GloVe…
GloVe has been applied to the training & testing datasets!
-----

Running algorithm on le training & testing datasets (with pretrained model
embeddings)…
Running Logistic Regression algorithm, version A (Word2Vec)…
..First embeddings are done!
Running Logistic Regression algorithm, version B (GloVe)…

c:\tools\miniconda3\lib\site-packages\sklearn\linear_model\_logistic.py:460:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

..First embeddings are done!
…All Done!
-----

Here are le results [Logistic Regression /w two (2) pretrained model-based
embedding classification]…

Logistic Regression Algorithm, Version A: Word2Vec Pretrained Model-based
Embeddings Performance, Metrics, & Results:
…Accuracy was found to be,  86.3 %,
…F1 Score was found to be:  0.86105476673428 ,
…with a Confusion Matrix:
 [[1754  246]
 [ 302 1698]] ,
…& lastly, the classification Report:
               precision    recall  f1-score   support
```

```
           0       0.85      0.88      0.86      2000
           1       0.87      0.85      0.86      2000

    accuracy                           0.86      4000
   macro avg       0.86      0.86      0.86      4000
weighted avg       0.86      0.86      0.86      4000

-----

Logistic Regression Algorithm, Version B: GloVe Pretrained Model-based
Embeddings Performance, Metrics, & Results:
…Accuracy was found to be,  69.69999999999999 %,
…F1 Score was found to be:  0.7313829787234042 ,
…with a Confusion Matrix:
 [[1138  862]
 [ 350 1650]] ,
…& lastly, the classification Report:
               precision    recall  f1-score   support

           0       0.76      0.57      0.65      2000
           1       0.66      0.82      0.73      2000

    accuracy                           0.70      4000
   macro avg       0.71      0.70      0.69      4000
weighted avg       0.71      0.70      0.69      4000

-----
```

1.1.4 Text-Classification Model Performance Analysis & Discussion

Initial Data Results, Metrics, & Analysis Using Logistic Regression for both Version A, which represents the `Word2Vec` model & Version B, which represents the `GloVe` model, we saw the following results:

Version A, `Word2Vec` Model:

```
Accuracy:  ~86.3%,
F1 Score:  0.86105476673428

Confusion Matrix:
[[1754  246]
[ 302 1698]]

Classification Report:
            precision    recall  f1-score   support

        0       0.85      0.88      0.86      2000
        1       0.87      0.85      0.86      2000
```

```
accuracy                                0.86      4000
macro avg       0.86      0.86      0.86      4000
weighted avg    0.86      0.86      0.86      4000
```

Version B, `GloVe` Model:

```
Accuracy: ~69.69%,
F1 Score: 0.7313829787234042

Confusion Matrix:
[[1138  862]
[ 350 1650]]

Classification Report:
            precision    recall  f1-score   support

         0       0.76      0.57      0.65      2000
         1       0.66      0.82      0.73      2000

accuracy                             0.70      4000
macro avg        0.71      0.70      0.69      4000
weighted avg     0.71      0.70      0.69      4000
```

Comparative Analysis & Discussion From the previous assignment, A1: Sentiment Analysis Text Classification, we saw the following results for the Logistic Regression algorithm, for Version A, which only had token vectorization, and Version B, which had the NLTK Vader sentiment analysis classifer applied to it:

From A1 Results: Logistic Regression Results (Version A) - No Classifiers Applied:

```
Accuracy: ~92.7%
F1 Score: ~0.92729

Confusion Matrix:
    [[923  77]
    [ 69 931]]

Classification Report:
            precision    recall  f1-score   support

        0       0.93      0.92      0.93      1000
        1       0.92      0.93      0.93      1000

accuracy                            0.93      2000
macro avg       0.93      0.93      0.93      2000
weighted avg    0.93      0.93      0.93      2000
```

From A1 Results: Logistic Regression Results (Version B) - NLTK Vader Sentiment Analysis Classifer Applied:

```
Accuracy:  ~92.8%
F1 Score:  0.9281437125748503

Confusion Matrix:
[[926  74]
 [ 70 930]]

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.93      0.93      1000
           1       0.93      0.93      0.93      1000

    accuracy                           0.93      2000
   macro avg       0.93      0.93      0.93      2000
weighted avg       0.93      0.93      0.93      2000
```

It appears that the Logistic Regression faired well each time from **A1 Results**, where we interestingly see decreases in performance in **A2 Results**, when we compare the accuracy of ~86.3% for the `Word2Vec` model vs. the ~69.69% for the `GloVe` pretrained model embeddings.

Recalling from the *A1 Results* analysis:

```
Contrarywise, the Logistic Regression algorithm of Version A was accurate ~96% of the time,
...which showcases a highly significant increase in both relative (in comparsion to Gaussian Na

In Version B, where [NLTK Vader](https://www.nltk.org/_modules/nltk/sentiment/vader.html),
...Sentiment Analysis was applied as a classifer to both the training & testing datasets, we se
...in both algorithms (as seen above for Version B results),
...where we see an increase of ~0.11% in accuracy for the Gaussian Näive Bayes algorithm
...& an increase of ~0.01% in accuracy for Logistic Regression.
```

However, although having lower accuracies for both models is, in the grand perspective, not great - it is at least *relatively* good, for the sake of model analysis, that we are able to see more than a ~0.01% in deviation for accuracy between the two (2) pretrained models, such that we can see the possible difference in effectiveness in these two models, for the specific training & testing dataset we have been utilizing.

Text-Classification Challenges & Limitations The initial challenges were due to the process of implementing the visualization using t-SNE, where one of its dependencies, threadpoolctl, needed to be upgraded to 3.1.0 in order for the t-SNE `fit_transform` to properly recognize & properly analyze the pretrained models.

This particular error took the majority of the whole time spent on the assignment, where a back-and-forth re-programming downward spiral occurred, before I had swallowed my pride & resorted to looking up the specific NoneType attribute error on *StackOverflow*, which, much to the thanks of others who have suffered alike, another programmer had found the solution.

Other than this procedural challenge, a limitation specific to the implementation of the pretrained model-based embeddings were due to a possible lack of required preprocessing in order to meet or succeed the rates of success as seen from the *A1 Results*, in terms of accuracy.

Discussion for Future Performance & Efficacy Improvements With more time, I think that there would have most likely been definite improvements in accuracy if preprocessing was much more closely matched to that of the preprocessing that was applied to the training corpus for each of our respective two (2) pretrained models that we've used for embeddings in question.

Specifically, for our two (2) `Word2Vec` & `GloVe` models, upon further reading about the model details & specifications on *Hugging Face* for word2vec-google-news-300 & glove-wiki-gigaword-300 (also the *Stanford* paper, *GloVe: Global Vectors for Word Representation*), a little bit more preprocessing may have made a significant difference in reaching higher levels of accuracy & precision, perhaps.

1.1.5 References & Resources

Libraries & Dependencies

`matplotlib.pyplot`
`numpy`
`pandas`

sklearn.naive_bayes.GaussianNB

sklearn.linear_model.LogisticRegression

sklearn.model_selection.train_test_split

sklearn.feature_extraction.text.CountVectorizer

sklearn.metrics.f1_score

sklearn.metrics.accuracy_score

sklearn.metrics.confusion_matrix

sklearn.metrics.classification_report

nltk

nbconvert

gensim

t-SNE

References & Credits *NLP Tutorial for Text Classification in Python* by Vijaya Rani

Using CountVectorizer to Extracting Features from Text by *GeeksforGeeks*

Google Code - Archive: word2vec

GloVe: Global Vectors for Word Representation

Credits to GitHub Copilot & ChatGPT for code implementation assistance.

Special Thanks Fixing *sklearn ImportError: No module named _check_build*

Fixing super random 'NoneType' has no attribute 'split' error by upgrading t-SNE dependency threadpoolctl to 3.1.0 or above

Extra Stuff

1.1.6 A2 Results: Raw Output from `Word2Vec` & GloVe Embedding Results, using the Logistic Regression Algorithm

```
Logistic Regression Algorithm, Version A: Word2Vec Pretrained Model-based Embeddings Performan
...Accuracy was found to be,  86.3 %,
...F1 Score was found to be:  0.86105476673428 ,
...with a Confusion Matrix:
[[1754  246]
[ 302 1698]] ,
...& lastly, the classification Report:
            precision    recall  f1-score   support

        0       0.85      0.88      0.86      2000
        1       0.87      0.85      0.86      2000

    accuracy                           0.86      4000
macro avg       0.86      0.86      0.86      4000
weighted avg       0.86      0.86      0.86      4000

-----

Logistic Regression Algorithm, Version B: GloVe Pretrained Model-based Embeddings Performance,
...Accuracy was found to be,  69.69999999999999 %,
...F1 Score was found to be:  0.7313829787234042 ,
...with a Confusion Matrix:
[[1138  862]
[ 350 1650]] ,
...& lastly, the classification Report:
            precision    recall  f1-score   support

        0       0.76      0.57      0.65      2000
        1       0.66      0.82      0.73      2000

    accuracy                           0.70      4000
macro avg       0.71      0.70      0.69      4000
weighted avg       0.71      0.70      0.69      4000

-----
```

From A1 Results for Reference: **Initial Full 80k-Row Processing Results Raw Output**

```
Algorithm #1, Version A: Gaussian Näive Bayes Performance, Metrics, & Results:
```

```
...Accuracy was found to be,  59.199999999999996 %,
...F1 Score was found to be:  0.3664596273291925 ,
...with a Confusion Matrix:
[[948  52]
[764 236]] ,
...& lastly, the classification Report:
            precision    recall  f1-score   support

        0       0.55      0.95      0.70      1000
        1       0.82      0.24      0.37      1000

    accuracy                           0.59      2000
macro avg       0.69      0.59      0.53      2000
weighted avg       0.69      0.59      0.53      2000

-----

Algorithm #2, Version A: Logistic Regression Performance, Metrics, & Results:
...Accuracy was found to be,  92.7 %,
...F1 Score was found to be:  0.9272908366533865 ,
...with a Confusion Matrix:
[[923  77]
[ 69 931]] ,
...& lastly, the classification Report:
            precision    recall  f1-score   support

        0       0.93      0.92      0.93      1000
        1       0.92      0.93      0.93      1000

    accuracy                           0.93      2000
macro avg       0.93      0.93      0.93      2000
weighted avg       0.93      0.93      0.93      2000

-----

Algorithm #1, Version B: Gaussian Näive Bayes Performance, Metrics, & Results:
...Accuracy was found to be,  59.3 %,
...F1 Score was found to be:  0.36899224806201547 ,
...with a Confusion Matrix:
[[948  52]
[762 238]] ,
...& lastly, the classification Report:
            precision    recall  f1-score   support

        0       0.55      0.95      0.70      1000
        1       0.82      0.24      0.37      1000

    accuracy                           0.59      2000
```

```
macro avg       0.69      0.59      0.53      2000
weighted avg       0.69      0.59      0.53      2000

-----

Algorithm #2, Version B: Logistic Regression Performance, Metrics, & Results:
...Accuracy was found to be,  92.80000000000001 %,
...F1 Score was found to be:  0.9281437125748503 ,
...with a Confusion Matrix:
[[926  74]
[ 70 930]] ,
...& lastly, the classification Report:
            precision    recall  f1-score   support

        0       0.93      0.93      0.93      1000
        1       0.93      0.93      0.93      1000

    accuracy                           0.93      2000
macro avg       0.93      0.93      0.93      2000
weighted avg       0.93      0.93      0.93      2000

-----
```

[27]:

```
##### Juypter Notebook -> PDF Conversion thingy

#!pip install nbconvert
!jupyter nbconvert --to pdf a2-Word2Vec-and-gloVe-embeddings-dan-jang.ipynb
```

```
[NbConvertApp] Converting notebook a2-Word2Vec-and-gloVe-embeddings-dan-
jang.ipynb to pdf
[NbConvertApp] Support files will be in a2-Word2Vec-and-gloVe-embeddings-dan-
jang_files\
[NbConvertApp] Making directory .\a2-Word2Vec-and-gloVe-embeddings-dan-
jang_files
[NbConvertApp] Making directory .\a2-Word2Vec-and-gloVe-embeddings-dan-
jang_files
[NbConvertApp] Making directory .\a2-Word2Vec-and-gloVe-embeddings-dan-
jang_files
[NbConvertApp] Making directory .\a2-Word2Vec-and-gloVe-embeddings-dan-
jang_files
[NbConvertApp] Writing 85396 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | b had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 234209 bytes to a2-Word2Vec-and-gloVe-embeddings-dan-
```

jang.pdf