Sklearn Logistic Regression with Tf-Idf vectorization

```
from scipy import sparse
from sklearn.linear model import LogisticRegression
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import ConfusionMatrixDisplay, f1_score
from collections import Counter
import numpy as np
import operator
import nltk
import math
from scipy.stats import norm
import jieba
import regex as re
from google.colab import drive
drive.mount('/content/drive')
    Mounted at /content/drive
%cd "/content/drive/MyDrive/Info 159 Notebooks/Annotation Project - Leiden Weibo Corpus/AP4"
    /content/drive/MyDrive/Info 159 Notebooks/Annotation Project - Leiden Weibo Corpus/AP4
stopwords_file = "stopwords-zh.txt"
stopwords = set(line.strip() for line in open(stopwords_file))
print(stopwords)
     {'还是','替','那么些','根据','9','乃','若','呵','总而言之','比方','鄙人','六','之一','出于','人家','接着','此','然而','已矣
def load_data(filename):
   X = []
   Y = []
   with open(filename, encoding="utf-8") as file:
       for line in file:
           cols = line.split("\t")
           idd = cols[0]
           label = cols[2].lstrip().rstrip()
           text = cols[3]
           X.append(text)
           Y.append(label)
   return X, Y
def analyzer(text):
   text = "".join([n for n in re.findall(r'[\u4e00-\u9fff]+', text)])
   # text = "".join([n for n in text if n not in stopwords])
   text = jieba.lcut(text)
   return text
def confidence_intervals(accuracy, n, significance_level):
   critical_value=(1-significance_level)/2
   z_alpha=-1*norm.ppf(critical_value)
   se=math.sqrt((accuracy*(1-accuracy))/n)
   return accuracy-(se*z_alpha), accuracy+(se*z_alpha)
tf_idf = TfidfVectorizer(analyzer = analyzer)
trainingFile = "./splits/train.txt"
devFile = "./splits/dev.txt"
testFile = "./splits/test.txt"
trainX, trainY = load_data(trainingFile)
devX, devY = load_data(devFile)
testX, testY = load_data(testFile)
trainX = tf_idf.fit_transform(trainX)
devX = tf_idf.transform(devX)
testX = tf_idf.transform(testX)
```

```
Building prefix dict from the default dictionary ...
     DEBUG: jieba: Building prefix dict from the default dictionary ...
     Dumping model to file cache /tmp/jieba.cache
     DEBUG:jieba:Dumping model to file cache /tmp/jieba.cache
     Loading model cost 0.729 seconds.
     DEBUG: jieba: Loading model cost 0.729 seconds.
     Prefix dict has been built successfully.
     DEBUG: jieba: Prefix dict has been built successfully.
print(tf_idf.vocabulary_)
     {'为什么': 138, '每次': 1461, '不': 78, '在': 693, '中国': 130, '都': 2165, '会': 255, '他们': 235, '家': 880, '田鸡': 1670, '爱喝': 1601,
Cs = [1e-4, 1e-3, 1e-2, 1e-1, 1, 10, 100, 1000, 10000, 100000]
best_score = 0.
best_model = None
for C in Cs:
   log_reg = LogisticRegression(C=C, class_weight='balanced', max_iter=10000, random_state=159)
    model = log_reg.fit(trainX, trainY)
   score = log_reg.score(devX, devY)
    if score > best_score:
        best_model = model
        best_score = score
test_score = best_model.score(testX, testY)
print(test_score)
     0.43
print(best_model.get_params())
lower, upper=confidence_intervals(test_score, len(testY), .95)
print(lower, test_score, upper)
     ('C': 1, 'class_weight': 'balanced', 'dual': False, 'fit_intercept': True, 'intercept_scaling': 1, 'l1_ratio': None, 'max_iter': 10000,
     0.3329669356893162\ 0.43\ 0.5270330643106838
ConfusionMatrixDisplay.from_estimator(best_model, testX, testY, labels=best_model.classes_, xticks_rotation='vertical')
     <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f0f6aa91c90>
                advertisement -
                                                                                0
                                                                                          14
                entertainment
                      feelings
                                                                                          12
                       finance
                                                                                          10
                  food & drink
      True label
                       gaming
                                                                                          8
                      lifestyle
                                                                       0
                                                                                          6
                                                                 16
                         none
         science & technology -
                       society
                                                                                          2
                        sports
                                                        gaming
                                               finance
                                                                  none
                                 advertisement
                                     entertainment
                                          feelings
                                                   & drink
                                                             ifestyle
                                                                      science & technology
                                                                           society
                                                   poog
                                                  Predicted label
```

```
reverse_vocab=[None]*len(best_model.coef_[0])
for k in tf_idf.vocabulary_:
    reverse_vocab[tf_idf.vocabulary_[k]]=k
for i, cat in enumerate(best_model.classes_):
```

```
weights=best model.coef [i]
   for feature, weight in list(reversed(sorted(zip(reverse_vocab, weights), key = operator.itemgetter(1))))[:10]:
      print("%s\t%.3f\t%s" % (cat, weight, feature))
    gaming 0.560
                   招讨
    gaming 0.551
                   NINI
    lifestyle
                   0.416
                           想
                           去
    lifestyle
                   0.410
    lifestyle
                   0.384
                           在
    lifestyle
                   0.353
                           不
    lifestvle
                   0.345
    lifestyle
                   0.320 呀
    lifestyle
                    0.313
    lifestyle
                   0.309
                   0.306
                          喝多
    lifestyle
    lifestyle
                   0.294
                   图片
    none
           1.248
    none
            1.248
                    分享
            0.489
                   阳朔
            0.489
                    号线
    none
                   膃
    none
            0.468
    none
            0.437
                   酷
            0.388
                   准备
    none
            0.352
                   圖片
    none
    none
            0.346
    none
            0.346
                   射手
    science & technology
                          1.592
    science & technology
                                   软件
    science & technology
                           1.380
    science & technology
                          1.380
                                   微盘
    science & technology
                           1.380
                                   [里][里]
    science & technology
                          1.281
    science & technology
                                   传到
                           1.279
    science & technology
                           1.278
                                   用
                           0.952
    science & technology
                                   路上
    science & technology
                           0.862
    society 1.764
    society 1.334
    society 0.953
                   珈
    society 0.953
                   玮
    society 0.923
                    浪漫
    society 0.923
                   トア・ト
    society 0.923
                   全是
    society 0.887
                    喜糖
    society 0.855
    society 0.834
                   可怕
    sports 2.256
                   斯科尔斯
    sports 1.381
                   万星
    sports 1.381
    sports 0.889
    sports 0.889
                   第轮
    sports 0.833
    sports 0.806
     sports 0.725
                    믁
    sports 0.717
                   上海
    sports 0.666
                   面料
scores = f1_score(testY, best_model.predict(testX), labels=best_model.classes_, average=None, zero_division=0)
for i, cl in enumerate(best_model.classes_):
   print(f"{cl}: {scores[i]}")
print("overall weighted: %f" % f1_score(testY, best_model.predict(testX), labels=best_model.classes_, average='weighted', zero_division=0))
    advertisement: 0.3333333333333333
    entertainment: 0.1111111111111111
    feelings: 0.33333333333333333
    finance: 0.0
    food & drink: 0.0
    gaming: 0.5217391304347825
    lifestyle: 0.416666666666663
    none: 0.72727272727274
    science & technology: 0.0
    society: 0.0
    sports: 0.666666666666666
    overall weighted: 0.403542
```

```
Majority Class
```

```
from sklearn.dummy import DummyClassifier
trainingFile = "./splits/train.txt"
devFile = "./splits/dev.txt"
testFile = "./splits/test.txt"
trainX, trainY = load_data(trainingFile)
devX, devY = load data(devFile)
testX, testY = load_data(testFile)
clf = DummyClassifier(strategy='most_frequent', random_state=159)
clf.fit(trainX, trainY)
majority_class = clf.score(trainX, trainY)
dev_score = clf.score(devX, devY)
test_score = clf.score(testX, testY)
print(f"majority_class: {majority_class}, dev accuracy: {dev_score}, test accuracy: {test_score}")
     majority class: 0.24666666666666667, dev accuracy: 0.23, test accuracy: 0.22
lower, upper=confidence_intervals(test_score, len(testY), .95)
print(lower, test_score, upper)
     0.13880921643246003 0.22 0.30119078356754
ConfusionMatrixDisplay.from_estimator(clf, testX, testY, labels=best_model.classes_, xticks_rotation='vertical')
     <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f7e0b0885e0>
                                                                                             25
                advertisement
                                                          0
                 entertainment
                                                          0
                                                                    0
                                                              26
                       feelings
                                                                                             20
                                       0
                                                          0
                       finance
                  food & drink
                                                     0
                                                                                             15
      True label
                                                                         0
                       gaming
                                                              22
                                            0
                       lifestyle
                                                                                             10
                                                               18
                          none
         science & technology
                                  0
                                                                                             5
                        society
                                  0
                                                     0
                                                          0
                                                               3
                         sports
                                                          0
                                           feelings
                                                finance
                                                                    none
                                                                                  sports
                                      entertainment
                                                     & drink
                                 advertisement
                                                               ifestyle
                                                                        science & technology
                                                                             society
                                                     food
```

TextCNN

Predicted label

```
Requirement \ already \ satisfied: \ numpy \ in \ /usr/local/lib/python 3.10/dist-packages \ (from \ fasttext) \ (1.22.4)
     Building wheels for collected packages: fasttext
       Building wheel for fasttext (setup.py) ... done
       Created wheel for fasttext: filename=fasttext-0.9.2-cp310-cp310-linux x86 64.whl size=4393275 sha256=17127eb85bf8e75bfa7c63591eaddf654
       Stored in directory: /root/.cache/pip/wheels/a5/13/75/f811c84a8ab36eedbaef977a6a58a98990e8e0f1967f98f394
     Successfully built fasttext
     Installing collected packages: pybind11, fasttext
     Successfully installed fasttext-0.9.2 pybind11-2.10.4
    6
import os
os.environ['CUDA LAUNCH BLOCKING'] = "1"
from collections import Counter
import jieba
import regex as re
import fasttext.util
import torch
import torch.nn as nn
import torch.nn.functional as F
from sklearn.preprocessing import LabelEncoder
import numpy as np
import random
from scipy.stats import norm
import math
%cd "/content/drive/MyDrive/Annotation Project - Leiden Weibo Corpus/AP4"
     [Errno 2] No such file or directory: '/content/drive/MyDrive/Annotation Project - Leiden Weibo Corpus/AP4'
     /content/drive/MyDrive/Info 159 Notebooks/Annotation Project - Leiden Weibo Corpus/AP4
# uncomment the following line if its the first time downloading the fasttext model
# fasttext.util.download_model('zh', if_exists='ignore')
ft = fasttext.load_model('cc.zh.300.bin')
     Warning: `load_model` does not return WordVectorModel or SupervisedModel any more, but a `FastText` object which is very similar.
def tokenizer(text):
    text = "".join([n for n in re.findall(r'[\u4e00-\u9fff]+', text)])
   text = jieba.lcut(text)
   return text
def load data(filename):
   X = []
   Y = []
   with open(filename, encoding="utf-8") as file:
        for line in file:
            cols = line.split("\t")
            idd = cols[0]
            label = cols[2].lstrip().rstrip()
            text = cols[3]
            X.append(text)
            Y.append(label)
   return X, Y
def confidence_intervals(accuracy, n, significance_level):
   critical_value=(1-significance_level)/2
    z_alpha=-1*norm.ppf(critical_value)
    se=math.sqrt((accuracy*(1-accuracy))/n)
   return accuracy-(se*z_alpha), accuracy+(se*z_alpha)
trainingFile = "./splits/train.txt"
devFile = "./splits/dev.txt"
testFile = "./splits/test.txt"
trainX, trainY = load_data(trainingFile)
devX, devY = load data(devFile)
testX, testY = load_data(testFile)
trainX = list(map(tokenizer, trainX))
devX = list(map(tokenizer, devX))
```

```
testX = list(map(tokenizer, testX))
vocab = Counter([word for sentence in trainX for word in sentence])
vocab_size = len(vocab)
print(vocab_size)
print(vocab)
print(trainX)
    Counter({'的': 263, '了': 182, '我': 131, '你': 93, '是': 74, '在': 61, '啊': 43, '都': 37, '有': 35, '就': 32, '也': 27, '不': 26, '吧':
    [['为什么', '每次', '不', '在', '中国', '都', '会', '在', '他们', '家', '田鸡', '爱喝', '乙醇', '的', '甲醇'], ['小妞', '曼陀罗', '你', '厉害
def tokens_to_embeddings(tokens, vocab=vocab, ft=ft, embedding_dim=300, max_tokens=200):
   embeddings = []
   for i in range(max_tokens):
       if i < len(tokens):</pre>
          if tokens[i] in vocab.keys():
              embeddings.append(ft.get word vector(tokens[i]))
          else:
              embeddings.append(np.random.rand(embedding_dim))
       else:
          embeddings.append(np.zeros(embedding_dim))
   return np.array(embeddings)
trainX = np.array(list(map(tokens_to_embeddings, trainX)))
devX = np.array(list(map(tokens to embeddings, devX)))
testX = np.array(list(map(tokens_to_embeddings, testX)))
le = LabelEncoder()
trainY = le.fit_transform(trainY)
devY = le.transform(devY)
testY = le.transform(testY)
print(le.classes_)
print(len(le.classes_))
    ['advertisement' 'entertainment' 'feelings' 'finance' 'food & drink'
      gaming' 'lifestyle' 'none' 'science & technology' 'society' 'sports']
print(trainY)
    [6476564116666102527555
                   6 0 1
                           6 6 6 6 4 1 4 7
                                                 0
                   7 6 6 6 1 6 6 6 1
                                           6 5 6 7
           6 9 6 6 6 1 1 8 9 10 7
                                           5 10 5 0
                                        1
              7 10 7 2
                              2 5
                        2
                           2
                                   2
                                      2
                                        2
                                           2 2
                                                   2
                                                      0
           2
                6 5 7
                           2
                                5 4 5 4
                                           6 4
                                                2 1
                              2 2
                5 2 4 2 0
                                        2
                                           0 10
              2 6 6 6 6 7
                              7 6 6 2 6 0 7
                                                   2
                                                     a a
        0 2 3
                7 1 6 1 9 2 2 0 2 6 6 4 6 7
                                                      2 10 6 5 6 2
                5 2 10
                        7 6 0
                                6
                                   6 6 6
      6 6 5 2 4 6 6 6 6 10 0 4 1 2 6 6 9 2 2
           print(trainX.shape)
    (300, 200, 300)
class TextCNN(nn.Module):
   def __init__(self, ):
       super(TextCNN, self).__init__()
       filter_sizes = [3,5,7,9,11]
       ch_in = 1
       num filters = 400
       num_classes = 11
       dropout = 0.5
       embedding dimension = 300
       # self.embedding = nn.Embedding(vocab_size, embedding_dimension)
       self.convs = nn.ModuleList(
```

```
[nn.Conv2d(ch_in, num_filters, (size, embedding_dimension)) for size in filter_sizes])
        self.dropout = nn.Dropout(dropout)
        self.fc = nn.Linear(len(filter_sizes) * num_filters, num_classes)
   def forward(self, x):
        \# x = self.embedding(x)
        x = x.unsqueeze(1)
        x = [F.relu(conv(x)).squeeze(3) for conv in self.convs]
        x = [F.max\_pool1d(item, item.size(2)).squeeze(2) for item in x]
        x = torch.cat(x, 1)
        x = self.dropout(x)
        logits = self.fc(x)
        return logits
def get_batches(all_x, all_y, batch_size=50):
   batches_x=[]
   batches_y=[]
    for i in range(0, len(all_x), batch_size):
        current_batch=[]
        batch_x=all_x[i:i+batch_size]
        batch_y=all_y[i:i+batch_size]
        batches_x.append(torch.FloatTensor(batch_x).cuda())
        batches_y.append(torch.LongTensor(batch_y).cuda())
    return batches_x, batches_y
def evaluate(model, x, y):
   model.eval()
   corr = 0.
   total = 0.
   with torch.no_grad():
        for x, y in zip(x, y):
           y_preds=model.forward(x)
            for idx, y_pred in enumerate(y_preds):
                prediction=torch.argmax(y_pred)
                if prediction == y[idx]:
                   corr += 1.
                total+=1
    return corr/total, total
import os
import sys
import torch
import torch.nn.functional as F
def train(train_x, train_y, dev_x, dev_y, model):
   model.cuda()
   batch_x, batch_y = get_batches(train_x, train_y)
   dev_batch_x, dev_batch_y = get_batches(dev_x, dev_y)
   optimizer = torch.optim.Adam(model.parameters(), lr=1e-5)
    cross_entropy=nn.CrossEntropyLoss()
   num_epochs=1000
   best_dev_acc = 0.
   patience=2000
   best_epoch=0
    for epoch in range(num_epochs):
        model.train()
        # Train
        for x, y in zip(batch_x, batch_y):
           x = x.cuda()
            y = y.cuda()
            logits = model(x)
```

```
loss = cross_entropy(logits, y)
           optimizer.zero_grad()
           loss.backward()
           optimizer.step()
        # Evaluate
        train_accuracy, _= evaluate(model, batch_x, batch_y)
        dev_accuracy, _= evaluate(model, dev_batch_x, dev_batch_y)
        if epoch % 10 == 0:
           print("Epoch %s, train accuracy: %.3f, dev accuracy: %.3f" % (epoch, train accuracy, dev accuracy))
           if dev_accuracy > best_dev_acc:
               torch.save(model.state_dict(), 'textcnn.pt')
               best_dev_acc = dev_accuracy
               best epoch=epoch
        if epoch - best_epoch > patience:
           print("No improvement in dev accuracy over %s epochs; stopping training" % patience)
   model.load_state_dict(torch.load('textcnn.pt'))
   print("\nBest Performing Model achieves dev accuracy of : %.3f" % (best_dev_acc))
model = TextCNN()
model = train(trainX, trainY, devX, devY, model)
     Epoch 0, train_accuracy: 0.083, dev accuracy: 0.090
     Epoch 10, train_accuracy: 0.457, dev accuracy: 0.230
     Epoch 20, train_accuracy: 0.477, dev accuracy: 0.230
    Epoch 30, train_accuracy: 0.493, dev accuracy: 0.240
     Epoch 40, train_accuracy: 0.497, dev accuracy: 0.240
    Epoch 50, train_accuracy: 0.513, dev accuracy: 0.240
    Epoch 60, train_accuracy: 0.527, dev accuracy: 0.240
     Epoch 70, train_accuracy: 0.533, dev accuracy: 0.240
    Epoch 80, train_accuracy: 0.557, dev accuracy: 0.240
    Epoch 90, train_accuracy: 0.577, dev accuracy: 0.240
     Epoch 100, train_accuracy: 0.673, dev accuracy: 0.310
    Epoch 110, train_accuracy: 0.703, dev accuracy: 0.310
    Epoch 120, train_accuracy: 0.720, dev accuracy: 0.310
     Epoch 130, train_accuracy: 0.730, dev accuracy: 0.320
    Epoch 140, train_accuracy: 0.753, dev accuracy: 0.320
    Epoch 150, train_accuracy: 0.777, dev accuracy: 0.330
    Epoch 160, train_accuracy: 0.790, dev accuracy: 0.330
    Epoch 170, train accuracy: 0.813, dev accuracy: 0.330
     Epoch 180, train_accuracy: 0.830, dev accuracy: 0.330
    Epoch 190, train_accuracy: 0.843, dev accuracy: 0.330
    Epoch 200, train_accuracy: 0.870, dev accuracy: 0.340
     Epoch 210, train_accuracy: 0.883, dev accuracy: 0.340
    Epoch 220, train_accuracy: 0.893, dev accuracy: 0.340
    Epoch 230, train_accuracy: 0.900, dev accuracy: 0.340
     Epoch 240, train_accuracy: 0.903, dev accuracy: 0.350
    Epoch 250, train_accuracy: 0.917, dev accuracy: 0.350
    Epoch 260, train_accuracy: 0.923, dev accuracy: 0.360
     Epoch 270, train_accuracy: 0.923, dev accuracy: 0.360
    Epoch 280, train_accuracy: 0.927, dev accuracy: 0.360
     Epoch 290, train_accuracy: 0.937, dev accuracy: 0.350
    Epoch 300, train_accuracy: 0.940, dev accuracy: 0.350
    Epoch 310, train accuracy: 0.943, dev accuracy: 0.350
    Epoch 320, train_accuracy: 0.957, dev accuracy: 0.360
     Epoch 330, train_accuracy: 0.957, dev accuracy: 0.360
     Epoch 340, train_accuracy: 0.957, dev accuracy: 0.360
     Epoch 350, train_accuracy: 0.967, dev accuracy: 0.360
    Epoch 360, train_accuracy: 0.970, dev accuracy: 0.360
    Epoch 370, train_accuracy: 0.970, dev accuracy: 0.370
     Epoch 380, train_accuracy: 0.970, dev accuracy: 0.380
     Epoch 390, train_accuracy: 0.973, dev accuracy: 0.380
    Epoch 400, train_accuracy: 0.973, dev accuracy: 0.370
     Epoch 410, train_accuracy: 0.977, dev accuracy: 0.380
    Epoch 420, train_accuracy: 0.977, dev accuracy: 0.380
    Epoch 430, train_accuracy: 0.980, dev accuracy: 0.380
    Epoch 440, train_accuracy: 0.990, dev accuracy: 0.380
    Epoch 450, train accuracy: 0.990, dev accuracy: 0.380
    Epoch 460, train_accuracy: 0.990, dev accuracy: 0.370
     Epoch 470, train_accuracy: 0.990, dev accuracy: 0.380
     Epoch 480, train_accuracy: 0.990, dev accuracy: 0.380
     Epoch 490, train_accuracy: 0.990, dev accuracy: 0.380
    Epoch 500, train_accuracy: 0.990, dev accuracy: 0.390
    Epoch 510, train_accuracy: 0.990, dev accuracy: 0.380
     Epoch 520, train_accuracy: 0.990, dev accuracy: 0.380
     Epoch 530, train_accuracy: 0.990, dev accuracy: 0.390
     Epoch 540, train_accuracy: 0.990, dev accuracy: 0.400
     Epoch 550, train accuracy: 0.990, dev accuracy: 0.390
     Epoch 560, train_accuracy: 0.990, dev accuracy: 0.380
```

```
test_batch_x, test_batch_y = get_batches(testX, testY)
accuracy, test_n=evaluate(model, test_batch_x, test_batch_y)

lower, upper=confidence_intervals(accuracy, test_n, .95)
print("Test accuracy for best dev model: %.3f, 95% CIs: [%.3f %.3f]\n" % (accuracy, lower, upper))

Test accuracy for best dev model: 0.380, 95% CIs: [0.285 0.475]
```

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