mlfornlp

November 1, 2020

```
[85]: import pandas as pd
     from sklearn.model_selection import train_test_split
     import re,collections
     from math import log
     from sklearn.decomposition import LatentDirichletAllocation
     from sklearn.feature_extraction.text import CountVectorizer
     import numpy as np
     from sklearn.linear_model import LogisticRegression
     from sklearn.metrics import accuracy_score, precision_score, recall_score, u
      from sklearn.cluster import KMeans
[40]: df_real = pd.read_csv('True.csv')
     df_real['RealNews?'] = True
     df_fake = pd.read_csv('Fake.csv')
     df fake['RealNews?'] = False
     df = df_real.append(df_fake)
[41]: df.columns
[41]: Index(['title', 'text', 'subject', 'date', 'RealNews?'], dtype='object')
[42]: df['document']=df[['title','text']].agg(' '.join,axis=1).apply(lambda x:x.
     df['text'] = df['text'].apply(lambda x:x.lower())
```

```
[43]: # CountVectorizer produces a feature matrix of token counts for text.

tf_vectorizer = CountVectorizer(stop_words='english')

x = tf_vectorizer.fit_transform(df['text'])

#fit the lda model with 10 topics

lda = LatentDirichletAllocation(n_components=10,random_state=0)

lda.fit(x)
```

```
[45]: #print the topics of lda model
print("\nTopics in LDA model:")
n_top_words = 20
tf_feature_names = tf_vectorizer.get_feature_names()
print_top_words(lda, tf_feature_names, n_top_words)
```

Topics in LDA model:

Topic #0: trump said republican house president senate republicans tax washington reuters white obama congress senator new democrats donald democratic year plan

Topic #1: police said year people city old told killed officers man family years arrested according death attack shooting group black officer

Topic #2: said state million 000 election government year money billion company new according percent companies reuters federal city public states vote

Topic #3: court said law trump president states obama federal order supreme

immigration justice judge administration department united case legal ban climate

Topic #4: trump said russia russian president fbi clinton intelligence investigation campaign house news election information committee comey security washington director department

Topic #5: clinton party hillary election percent said democratic voters sanders new campaign vote poll political presidential candidate support democrats polls year

Topic #6: trump people donald president just like twitter said obama white don know image time going news featured right com think

Topic #7: people women gun america like state american children new students law muslim school rights right group world just religious public

Topic #8: said government minister eu european reuters president israel britain united prime mexico trade states turkey union talks border parliament deal Topic #9: said united north military china state reuters korea states iran

president nuclear syria security trump government foreign war al told

```
[46]: print(lda.components_.shape)
len(tf_feature_names)

(10, 121690)

[46]: 121690
```

1.1 Most of the topics are related to politics. Topics such as fbi investigation, law on climate change, tax plan are found by the lda model. Its a good representation of real-world topics

```
[47]: #randomly sample 5 real news and 5 fake news
      df_sampled = df[df['RealNews?']==True].sample(n=5).append(df[df['RealNews?']
       \rightarrow']==False].sample(n=5))
[48]: df_sampled
[48]:
                                                           title \
      20627
             Trump visit to Britain still unfixed nine mont...
      8423
             Clinton leads Trump by eight points: Reuters/I...
      18904
             Iraq sends delegation to Iran 'to coordinate m...
             China busts underground bank in Guangzhou: Chi...
      19052
             Myanmar sees 'bad consequences' if U.S. impose...
      15771
             https://100percentfedup.com/video-hillary-aske...
      15507
      22173 BIGGER THAN SNOWDEN: Wikileaks 'Vault 7' Class...
      19886 WHOA! DEMOCRATIC Strategist Gives Crooked Hill...
      5524
              Sean Hannity Just Made A Bizarre Implication ...
      20061 WHY TRUMP SUPPORTERS ARE LAUGHING After WikiLe...
                                                            text
                                                                        subject \
      20627
             london (reuters) - nine months after prime min...
                                                                    worldnews
      8423
             new york (reuters) - democratic presidential c... politicsNews
             baghdad (reuters) - a top ranking delegation f...
      18904
                                                                   worldnews
             shanghai (reuters) - chinese police have broke...
                                                                   worldnews
      19052
             yangon (reuters) - proposed u.s. sanctions tar...
      15771
                                                                   worldnews
      15507
             https://100percentfedup.com/video-hillary-aske...
                                                                    politics
              he who controls the spice controls the univer...
      22173
                                                                     US News
             the most unpopular, deplorable woman in americ...
      19886
                                                                   left-news
             sean hannity made a bizarre implication during...
      5524
                                                                         News
             fans of #crookedhillary are not going to like ...
      20061
                                                                   left-news
```

```
date RealNews? \
20627
                                       September 8, 2017
                                                                 True
8423
                                         August 19, 2016
                                                                 True
18904
                                      September 27, 2017
                                                                 True
19052
                                      September 26, 2017
                                                                 True
15771
                                        November 3, 2017
                                                                 True
      https://100percentfedup.com/video-hillary-aske...
15507
                                                              False
                                           March 13, 2017
22173
                                                                False
                                              Oct 2, 2016
19886
                                                                False
5524
                                            July 10, 2016
                                                                False
20061
                                             Aug 28, 2016
                                                                False
                                                 document
20627 trump visit to britain still unfixed nine mont...
8423
       clinton leads trump by eight points: reuters/i...
18904
      iraq sends delegation to iran 'to coordinate m...
19052
      china busts underground bank in guangzhou: chi...
15771
      myanmar sees 'bad consequences' if u.s. impose...
15507
      https://100percentfedup.com/video-hillary-aske...
22173
      bigger than snowden: wikileaks 'vault 7' class...
19886 whoa! democratic strategist gives crooked hill...
5524
        sean hannity just made a bizarre implication ...
20061 why trump supporters are laughing after wikile...
```

2.1 Predict on test documents

```
[56]: #get topics for each document
    x_sampled = tf_vectorizer.transform(df_sampled['text'])
    topics_prob = lda.transform(x_sampled)
    #print(topics_prob.shape)
    docs_topics = np.argmax(topics_prob,axis=1)
    for i in range(len(docs_topics)):
        print("document {} belongs to topic {} }".format(i+1, docs_topics[i]))

    document 1 belongs to topic 8
    document 2 belongs to topic 5
```

```
document 2 belongs to topic 5 document 3 belongs to topic 9 document 4 belongs to topic 9 document 5 belongs to topic 9 document 6 belongs to topic 6 document 7 belongs to topic 4 document 8 belongs to topic 5 document 9 belongs to topic 6 document 10 belongs to topic 4
```

2.2 topic 9(US and North Korea nuclear war)is prevalent in real news articles. topics 4 and 6 are prevalent in fake news articles.

```
[58]: df_train, df_test = train_test_split(df, test_size=0.2, shuffle=True)
      print(df_train.shape,df_test.shape)
     (35918, 6) (8980, 6)
[68]: # CountVectorizer produces a feature matrix of token counts for text.
      tf vectorizer = CountVectorizer(stop words='english')
      x_train = tf_vectorizer.fit_transform(df_train['text'])
      #fit the lda model with 10 topics
      lda = LatentDirichletAllocation(n_components=10, random_state=0)
      lda.fit(x_train)
[68]: LatentDirichletAllocation(batch_size=128, doc_topic_prior=None,
                                evaluate_every=-1, learning_decay=0.7,
                                learning_method='batch', learning_offset=10.0,
                                max_doc_update_iter=100, max_iter=10,
                                mean_change_tol=0.001, n_components=10, n_jobs=None,
                                perp_tol=0.1, random_state=0, topic_word_prior=None,
                                total_samples=1000000.0, verbose=0)
[69]: #qet lda vectors for train and test docs
      x_train = lda.transform(x_train)
      x_test = tf_vectorizer.transform(df_test['text'])
      x_test = lda.transform(x_test)
      y_train,y_test= df_train['RealNews?'],df_test['RealNews?']
      print("x_train shape:",x_train.shape)
      print("y_train shape:",y_train.shape)
      print("x_test shape:",x_test.shape)
      print("y_test shape:",y_test.shape)
     x_train shape: (35918, 10)
     y_train shape: (35918,)
     x_test shape: (8980, 10)
     y_test shape: (8980,)
[70]: #train the logistic regression clf
      lr = LogisticRegression(random_state=0)
      lr.fit(x_train,y_train)
      #prediction
      y_pred = lr.predict(x_test)
      y_prob = lr.predict_proba(x_test)[:,1]
```

```
#model evaluation
      print("Logistic regression model performance on lda vectors:")
      print("Accuracy score is {}".format(accuracy_score(y_test,y_pred)))
      print("Precision score is {}".format(precision_score(y_test, y_pred)))
      print("Recall score is {}".format(recall_score(y_test, y_pred)))
      print("F1 score is {}".format(f1_score(y_test, y_pred)))
      print("Area Under the Curve(ROC curve) is {}".
       →format(roc_auc_score(y_test,y_prob)))
      tn, fp, fn, tp = confusion_matrix(y_test,y_pred).ravel()
      print("true negative", tn)
      print("false positive", fp)
      print("false negative", fn)
      print("true positive", tp)
      specificity = tn / (tn+fp)
      print("specificity is {}".format(specificity))
     /home/vijay/anaconda3/lib/python3.7/site-
     packages/sklearn/linear_model/logistic.py:432: FutureWarning: Default solver
     will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
       FutureWarning)
     Logistic regression model performance on lda vectors:
     Accuracy score is 0.884075723830735
     Precision score is 0.8751450452541193
     Recall score is 0.8823116518483856
     F1 score is 0.8787137364557847
     Area Under the Curve(ROC curve) is 0.9532763508825242
     true negative 4168
     false positive 538
     false negative 503
     true positive 3771
     specificity is 0.8856778580535487
[81]: #get the most useful topics for classification
      topics_importance_score = lr.coef_
      useful_topics = np.flip(np.argsort(topics_importance_score))
      print("useful topics ranked from most useful to least useful", useful topics)
      print("scores for corresponding topics",topics_importance_score)
     useful topics ranked from most useful to least useful [[2 3 9 1 4 0 8 6 7 5]]
     scores for corresponding topics [[ 1.38789583 2.53022141 5.22121393
     4.06925796 1.45932434 -7.8030476
       -2.16746468 -6.43829936 -1.63321257 3.21623314]]
```

3.1 The top 3 most useful topics in classification of real or fake news is topic 2, topic 3 and topic 9.

```
[82]: #take only real news
       df real = df[df['RealNews?']==True]
[84]: #get the lda vectors for real news docs
       # CountVectorizer produces a feature matrix of token counts for text.
       tf_vectorizer = CountVectorizer(stop_words='english')
       x = tf_vectorizer.fit_transform(df_real['text'])
       #fit the lda model with 10 topics
       lda = LatentDirichletAllocation(n_components=10, random_state=0)
       lda.fit(x)
       x = lda.transform(x)
       print("shape of real news lda vectors is", x.shape)
      shape of real news lda vectors is (21417, 10)
[101]: #cluster the docs using k-means
       kmeans = KMeans(n_clusters=10, random_state=0)
       kmeans.fit(x)
[101]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
             n_clusters=10, n_init=10, n_jobs=None, precompute_distances='auto',
             random_state=0, tol=0.0001, verbose=0)
[103]: #get 5 documents from each cluster
       y_pred = kmeans.labels_
       n_clusters=10
       #stores docs index for each cluster
       docs_index_by_clusters=[]
       for i in range(n_clusters):
           #get all docs index for each cluster
          docs_index = np.where(y_pred==i)[0]
           #consider only 5 docs for each cluster
          docs_index = docs_index[:5]
          docs_index_by_clusters.append(docs_index)
       print(docs_index_by_clusters)
      [array([0, 4, 5, 7, 8]), array([ 919, 1227, 1345, 1349, 1351]), array([ 15, 34,
      66, 175, 178]), array([2, 3, 6, 9, 10]), array([43, 47, 61, 64, 65]),
      array([348, 363, 504, 571, 765]), array([33, 101, 105, 121, 128]), array([1,
      18, 20, 21, 22]), array([ 24, 452, 456, 461, 485]), array([447, 448, 549, 552,
      572])]
```

```
[106]: #print the titles of documents belonging to each cluster to find similarity
for i in range(len(docs_index_by_clusters)):
    print("document titles belonging to cluster",i)
    print("------")

    docs_indexes = docs_index_by_clusters[i]
    for j in docs_indexes:
        print(df_real.iloc[j]['title'])
    print("------")
```

document titles belonging to cluster 0

As U.S. budget fight looms, Republicans flip their fiscal script Trump wants Postal Service to charge 'much more' for Amazon shipments White House, Congress prepare for talks on spending, immigration Factbox: Trump on Twitter (Dec 29) - Approval rating, Amazon Trump on Twitter (Dec 28) - Global Warming

document titles belonging to cluster 1

North Korean defector pushes diplomatic solution in U.S. Congress North Korea not ready to meet with South Korea in Russia: agencies Turkey urges U.S. to review visa suspension as lira, stocks tumble Turkey's Erdogan says U.S. decision to suspend visa services 'upsetting' Turkey summons U.S. consulate worker for questioning: Anadolu

document titles belonging to cluster 2

Virginia officials postpone lottery drawing to decide tied statehouse election As Republicans aim to ride economy to election victory, a warning from voters in key district

In Georgia, battle of the 'Staceys' tests Democrats' future After Alabama upset, Democrats see new prospects in U.S. South Control of Virginia state House at stake as recounts begin

document titles belonging to cluster 3

Senior U.S. Republican senator: 'Let Mr. Mueller do his job'
FBI Russia probe helped by Australian diplomat tip-off: NYT
Trump says Russia probe will be fair, but timeline unclear: NYT
Alabama official to certify Senator-elect Jones today despite challenge: CNN
Jones certified U.S. Senate winner despite Moore challenge

document titles belonging to cluster 4

- U.S. House approves \$81 billion for disaster aid
- U.S. launches effort to reduce reliance on imports or critical minerals

White House says tax bill will not hurt Puerto Rico Fight over Alaska Arctic drilling has just begun, opponents vow Senator Cornyn trying to get Big Corn behind U.S. biofuels reform

document titles belonging to cluster 5

U.S. defense chief urges Pakistan to redouble efforts against militants U.S. embassy to Russia to resume some visa services after diplomatic row Russian envoy to U.S. to inspect San Francisco consulate: RIA Putin, Trump to discuss North Korea on Tuesday: IFX cites Kremlin aide White House condemns missile attacks on Saudi by Yemen's Houthis

document titles belonging to cluster 6

Callista Gingrich becomes Trump's envoy to pope as differences mount Trump strategy document says Russia meddles in domestic affairs worldwide Trump: U.S. has 'no choice' but to deal with North Korea arms challenge Trump to say in security speech that China is competitor: officials Trump officials brief Hill staff on Saudi reactors, enrichment a worry

document titles belonging to cluster 7

U.S. military to accept transgender recruits on Monday: Pentagon
U.S. appeals court rejects challenge to Trump voter fraud panel
Federal judge partially lifts Trump's latest refugee restrictions
Fyclusive: U.S. memo weakens guidelines for protecting immigrant children in

Exclusive: U.S. memo weakens guidelines for protecting immigrant children in court

Trump travel ban should not apply to people with strong U.S. ties: court

document titles belonging to cluster 8

Failed vote to oust president shakes up Peru's politics Britain's U.S. ambassador discussed Trump retweets with senior White House staff: source

British minister hopes condemnation of Trump tweet has impact Trump fires back at Britain's May: 'Don't focus on me'

Factbox: Who are Britain First, whose leader's posts Trump re-tweeted?

document titles belonging to cluster 9

Trump angers UK with truculent tweet to May after sharing far-right videos

- U.N. rights boss condemns "spreading hatred through tweets"
- U.S. calls Myanmar moves against Rohingya 'ethnic cleansing'
- U.S. hopes to pressure Myanmar to permit Rohingya repatriation
- U.S. Congress members decry 'ethnic cleansing' in Myanmar; Suu Kyi doubts allegations

4.1	There is some similarity between documents in each cluster. For example,
	docs in cluster 9 are about US opposition on Myanmar's ethnic cleansing,
	cluster 2 is about elections

[]: