LDA_for_Papersdata

July 20, 2024

1 1. Importing all the packages Required

[ ]:
```
import pyLDAvis
import pyLDAvis.gensim_models
import pickle
import pandas as pd
import os
import re
from wordcloud import WordCloud
import gensim
from gensim.utils import simple_preprocess
import nltk
from nltk.corpus import stopwords
from gensim import corpora
import warnings
warnings.filterwarnings("ignore")
```

2 2.Importing The Dataset

[ ]:
```
papers_data=pd.read_csv("E:/4TH_sem/ADA/LDA/papers.csv")
print("Shape of data",papers_data.shape)
```

```
Shape of data (7241, 7)
```

[ ]:
```
papers_data.head(10)
```

[ ]:
```
     id  year                                              title event_type  \
0     1  1987  Self-Organization of Associative Database and …        NaN
1    10  1987  A Mean Field Theory of Layer IV of Visual Cort…        NaN
2   100  1988  Storing Covariance by the Associative Long-Ter…        NaN
3  1000  1994  Bayesian Query Construction for Neural Network…        NaN
4  1001  1994  Neural Network Ensembles, Cross Validation, an…        NaN
5  1002  1994  Using a neural net to instantiate a deformable…        NaN
6  1003  1994           Plasticity-Mediated Competitive Learning        NaN
7  1004  1994  ICEG Morphology Classification using an Analog…        NaN
8  1005  1994  Real-Time Control of a Tokamak Plasma Using Ne…        NaN
9  1006  1994  Pulsestream Synapses with Non-Volatile Analogu…        NaN
```

```
                                            pdf_name          abstract  \
0  1-self-organization-of-associative-database-an…  Abstract Missing
1  10-a-mean-field-theory-of-layer-iv-of-visual-c…  Abstract Missing
2  100-storing-covariance-by-the-associative-long…  Abstract Missing
3  1000-bayesian-query-construction-for-neural-ne…  Abstract Missing
4  1001-neural-network-ensembles-cross-validation…  Abstract Missing
5  1002-using-a-neural-net-to-instantiate-a-defor…  Abstract Missing
6  1003-plasticity-mediated-competitive-learning.pdf  Abstract Missing
7  1004-iceg-morphology-classification-using-an-a…  Abstract Missing
8  1005-real-time-control-of-a-tokamak-plasma-usi…  Abstract Missing
9  1006-pulsestream-synapses-with-non-volatile-an…  Abstract Missing

                                          paper_text
0  767\n\nSELF-ORGANIZATION OF ASSOCIATIVE DATABA…
1  683\n\nA MEAN FIELD THEORY OF LAYER IV OF VISU…
2  394\n\nSTORING COVARIANCE BY THE ASSOCIATIVE\n…
3  Bayesian Query Construction for Neural\nNetwor…
4  Neural Network Ensembles, Cross\nValidation, a…
5  U sing a neural net to instantiate a\ndeformab…
6  Plasticity-Mediated Competitive Learning\n\nTe…
7  ICEG Morphology Classification using an\nAnalo…
8  Real-Time Control of a Tokamak Plasma\nUsing N…
9  Real-Time Control of a Tokamak Plasma\nUsing N…
```

[ ]:
```python
print(papers_data.columns)
```

```
Index(['id', 'year', 'title', 'event_type', 'pdf_name', 'abstract',
       'paper_text'],
      dtype='object')
```

3 3.Initial Pre-processing of Data

Perform removing puntuation and convert to lowercase

[ ]:
```python
import pandas as pd
import re

# Remove columns
columns_to_drop = ['id', 'event_type', 'pdf_name']
existing_columns = [col for col in columns_to_drop if col in papers_data.
 ↪columns]
if existing_columns:
    papers_data = papers_data.drop(columns=existing_columns)

# Remove punctuation
```

```
papers_data['paper_text_processed'] = papers_data['paper_text'].map(lambda x:␣
↪re.sub(r'[,.!?]', '', x))

# Lowercasing
papers_data['paper_text_processed'] = papers_data['paper_text_processed'].
↪map(lambda x: x.lower())

# Print the first few rows of the processed text
print(papers_data['paper_text_processed'].head())
```

```
648     a randomized algorithm for pairwise clustering…
3691    noise thresholds for spectral clustering\nsiva…
5194    estimating mixture models via mixtures of\npol…
1429    258\n\nseibert and waxman\n\nlearning aspect g…
1652    limiting form of the sample covariance\neigens…
Name: paper_text_processed, dtype: object
```

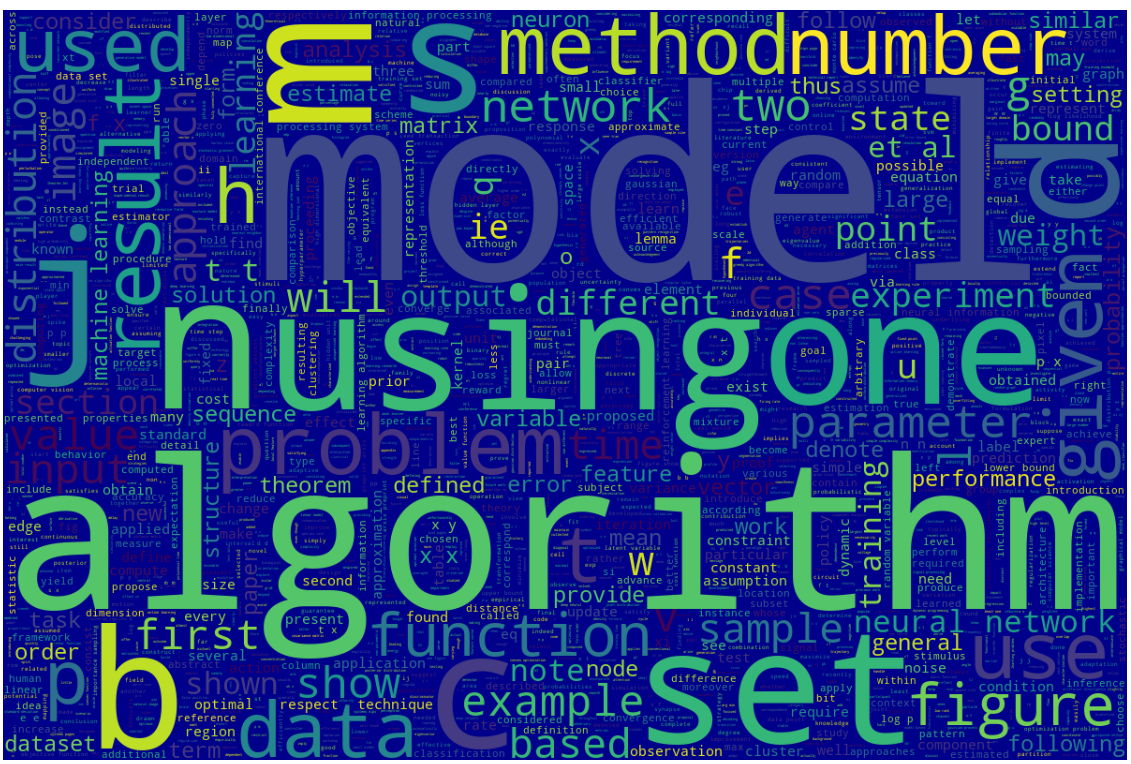
4 Word Cloud

[ ]:
```
string=','.join(list(papers_data['paper_text_processed'].values))

wordcloud=WordCloud(background_color='darkblue',max_words=8000,contour_width=4,contour_color='

wordcloud.generate(string)
wordcloud.to_image()
```

[ ]:



5 5. Initiating the LDA Analysis

[ ]:
```
stop_words=stopwords.words('english')
stop_words.
 ↪extend(['from','subject','re','edu','using','use','model','one','two','set'])

def sent_to_word(sentences):
    for sentence in sentences:
        yield(gensim.utils.simple_preprocess(str(sentence), deacc=True))

def remove_stopwords(texts):
    return[[word for word in simple_preprocess(str(doc))
            if word not in stop_words]for doc in texts]

data=papers_data.paper_text_processed.values.tolist()
data_words=list(sent_to_word(data))

data_words=remove_stopwords(data_words)
print(data_words[:1][0][:30])
```

```
['randomized', 'algorithm', 'pairwise', 'clustering', 'yoram', 'gdalyahu',
'daphna', 'weinshall', 'michael', 'werman', 'institute', 'computer', 'science',
'hebrew', 'university', 'jerusalem', 'israel', 'cshujiacil', 'abstract',
'present', 'stochastic', 'clustering', 'algorithm', 'based', 'pairwise',
'similarity', 'datapoints', 'method', 'extends', 'existing']
```

[ ]:
```
#create dictionary
id2word=corpora.Dictionary(data_words)
texts=data_words
corpus=[id2word.doc2bow(text) for text in texts]
print(corpus[:1][0][:30])
```

```
[(0, 1), (1, 1), (2, 1), (3, 1), (4, 1), (5, 2), (6, 2), (7, 1), (8, 1), (9, 1),
(10, 2), (11, 1), (12, 1), (13, 5), (14, 43), (15, 1), (16, 6), (17, 2), (18,
1), (19, 1), (20, 1), (21, 1), (22, 3), (23, 1), (24, 1), (25, 1), (26, 1), (27,
4), (28, 1), (29, 1)]
```

[ ]:
```
#showing the code
id2word
```

[ ]:
```
<gensim.corpora.dictionary.Dictionary at 0x1e0976c7500>
```

6 6.LDA MODEL TRAINING

[ ]:
```
from pprint import pprint

num_topics=10
lda_model=gensim.models.LdaMulticore(corpus=corpus,␣
    ↪id2word=id2word,num_topics=num_topics)
pprint(lda_model.print_topics())
doc_lda=lda_model[corpus]
```

```
[(0,
  '0.006*"data" + 0.005*"learning" + 0.004*"algorithm" + 0.004*"figure" + '
  '0.003*"time" + 0.003*"function" + 0.003*"number" + 0.003*"models" + '
  '0.003*"distribution" + 0.003*"training"'),
 (1,
  '0.006*"data" + 0.005*"learning" + 0.005*"algorithm" + 0.004*"time" + '
  '0.004*"number" + 0.003*"function" + 0.003*"figure" + 0.003*"log" + '
  '0.003*"network" + 0.003*"also"'),
 (2,
  '0.011*"learning" + 0.005*"data" + 0.005*"function" + 0.004*"algorithm" + '
  '0.004*"problem" + 0.004*"training" + 0.003*"matrix" + 0.003*"also" + '
  '0.003*"figure" + 0.003*"neural"'),
 (3,
  '0.007*"learning" + 0.005*"algorithm" + 0.005*"data" + 0.003*"time" + '
  '0.003*"first" + 0.003*"function" + 0.003*"problem" + 0.003*"figure" + '
  '0.003*"number" + 0.003*"used"'),
 (4,
  '0.007*"learning" + 0.005*"algorithm" + 0.005*"function" + 0.004*"data" + '
  '0.004*"number" + 0.004*"neural" + 0.004*"problem" + 0.003*"time" + '
  '0.003*"network" + 0.003*"networks"'),
 (5,
  '0.007*"learning" + 0.005*"function" + 0.005*"algorithm" + 0.004*"time" + '
  '0.004*"data" + 0.003*"distribution" + 0.003*"log" + 0.003*"problem" + '
  '0.003*"results" + 0.003*"also"'),
 (6,
  '0.007*"data" + 0.006*"algorithm" + 0.006*"learning" + 0.005*"function" + '
  '0.003*"number" + 0.003*"time" + 0.003*"results" + 0.003*"bound" + '
  '0.003*"figure" + 0.003*"also"'),
 (7,
  '0.007*"learning" + 0.005*"algorithm" + 0.005*"function" + 0.004*"network" + '
  '0.004*"time" + 0.004*"data" + 0.003*"number" + 0.003*"problem" + '
  '0.003*"figure" + 0.003*"based"'),
 (8,
  '0.007*"function" + 0.006*"learning" + 0.005*"data" + 0.005*"algorithm" + '
  '0.004*"figure" + 0.003*"number" + 0.003*"time" + 0.003*"problem" + '
  '0.003*"also" + 0.003*"models"'),
 (9,
  '0.006*"data" + 0.006*"algorithm" + 0.004*"function" + 0.004*"learning" + '
```

```
'0.003*"neural" + 0.003*"time" + 0.003*"problem" + 0.003*"input" + '
'0.003*"also" + 0.003*"given"')]
```

7 7. Analysing LDA MODEL

[ ]:
```python
import os
import pickle
import pyLDAvis
import pyLDAvis.gensim_models

# Define the path for saving the visualization data
output_dir = 'E:\\4TH_sem\\ADA\\LDA'  # Update this path to your directory
results_dir = os.path.join(output_dir, '02_Results')

# Create the directory if it does not exist
if not os.path.exists(results_dir):
    os.makedirs(results_dir)

pyLDAvis_data_filepath = os.path.join(results_dir, 'ldavis_prepared_' +
 ↪str(num_topics))

# Prepare LDA visualization
if True:  # Replace with your condition if needed
    LDAvis_prepared = pyLDAvis.gensim_models.prepare(lda_model, corpus, id2word)
    with open(pyLDAvis_data_filepath, 'wb') as f:
        pickle.dump(LDAvis_prepared, f)

# Load and save the visualization as an HTML file
with open(pyLDAvis_data_filepath, 'rb') as f:
    LDAvis_prepared = pickle.load(f)

pyLDAvis.save_html(LDAvis_prepared, os.path.join(output_dir, 'ldavis_prepared_'
 ↪+ str(num_topics) + '.html'))

# Display the prepared visualization (in Jupyter Notebook, for example)
LDAvis_prepared
```

[ ]:
```
PreparedData(topic_coordinates=              x         y  topics  cluster
Freq
topic
7      0.005127 -0.002622       1        1  21.066591
2      0.005215 -0.000775       2        1  14.620142
6      0.000045  0.006007       3        1  12.322246
4      0.002815 -0.003860       4        1  11.422165
9     -0.001055 -0.001650       5        1   9.149849
5     -0.002310  0.002451       6        1   8.205275
```

```
3      0.001539 -0.000031       7        1   6.995359
0     -0.007624 -0.003779       8        1   5.474013
8     -0.000397  0.005922       9        1   5.404880
1     -0.003355 -0.001664      10        1   5.339480, topic_info=
Term          Freq         Total  Category  logprob  loglift
135         data  3606.000000  3606.000000  Default  30.0000  30.0000
1104    learning  4934.000000  4934.000000  Default  29.0000  29.0000
241     function  3170.000000  3170.000000  Default  28.0000  28.0000
14     algorithm  3516.000000  3516.000000  Default  27.0000  27.0000
224       figure  2175.000000  2175.000000  Default  26.0000  26.0000
…          …            …            …        …        …        …
155    different    76.018420  1379.654198  Topic10  -6.2010   0.0314
2398    training    86.667683  1791.856065  Topic10  -6.0699  -0.0989
44         based    84.146779  1786.049969  Topic10  -6.0994  -0.1252
378       matrix    84.030723  1782.425637  Topic10  -6.1008  -0.1245
414       neural    83.569058  1877.352548  Topic10  -6.1063  -0.1819

[892 rows x 6 columns], token_table=       Topic      Freq     Term
term
28223       6  0.290504  acharya
27198       1  0.142140     acnn
27198       2  0.284279     acnn
27198       3  0.106605     acnn
27198       4  0.106605     acnn
…       …        …      …
15645       4  0.113509   zohary
15645       5  0.113509   zohary
15645       6  0.113509   zohary
15645       8  0.113509   zohary
15645      10  0.227017   zohary

[4128 rows x 3 columns], R=30, lambda_step=0.01, plot_opts={'xlab': 'PC1',
'ylab': 'PC2'}, topic_order=[8, 3, 7, 5, 10, 6, 4, 1, 9, 2])
```

[ ]:

```
# Extract and print top words for each topic
print("Top words for each topic:")
for topic_num in range(num_topics):
    print(f"Topic {topic_num}:")
    top_words = [word for word, _ in lda_model.show_topic(topic_num, topn=10)]
    print(top_words)
    print()

# Get the topic distribution for a specific document
document_id = 0  # Replace with the ID of the document you want to analyze
document_topics = lda_model.get_document_topics(corpus[document_id])
print(f"Document {document_id} Topic Distribution:")
for topic_num, prob in document_topics:
```

```python
    print(f"Topic {topic_num}: {prob:.4f}")
print()

# Create and save a summary of topics and their top keywords
topics_keywords = {}
for topic_num in range(num_topics):
    topics_keywords[topic_num] = [word for word, _ in lda_model.
 ↪show_topic(topic_num, topn=10)]

# Create a DataFrame with topic numbers and their top words
topics_summary = {
    'Topic': [],
    'Top Words': []
}
for topic_num, keywords in topics_keywords.items():
    topics_summary['Topic'].append(topic_num)
    topics_summary['Top Words'].append(', '.join(keywords))

df_topics_summary = pd.DataFrame(topics_summary)
df_topics_summary.to_csv(os.path.join(results_dir, 'topics_summary.csv'),␣
 ↪index=False)

print("Topics summary saved to 'topics_summary.csv'.")
```

```
Top words for each topic:
Topic 0:
['data', 'learning', 'algorithm', 'figure', 'time', 'function', 'number',
'models', 'distribution', 'training']

Topic 1:
['data', 'learning', 'algorithm', 'time', 'number', 'function', 'figure', 'log',
'network', 'also']

Topic 2:
['learning', 'data', 'function', 'algorithm', 'problem', 'training', 'matrix',
'also', 'figure', 'neural']

Topic 3:
['learning', 'algorithm', 'data', 'time', 'first', 'function', 'problem',
'figure', 'number', 'used']

Topic 4:
['learning', 'algorithm', 'function', 'data', 'number', 'neural', 'problem',
'time', 'network', 'networks']

Topic 5:
['learning', 'function', 'algorithm', 'time', 'data', 'distribution', 'log',
```

```
'problem', 'results', 'also']

Topic 6:
['data', 'algorithm', 'learning', 'function', 'number', 'time', 'results',
'bound', 'figure', 'also']

Topic 7:
['learning', 'algorithm', 'function', 'network', 'time', 'data', 'number',
'problem', 'figure', 'based']

Topic 8:
['function', 'learning', 'data', 'algorithm', 'figure', 'number', 'time',
'problem', 'also', 'models']

Topic 9:
['data', 'algorithm', 'function', 'learning', 'neural', 'time', 'problem',
'input', 'also', 'given']

Document 0 Topic Distribution:
Topic 1: 0.0375
Topic 3: 0.2726
Topic 4: 0.0341
Topic 5: 0.0566
Topic 6: 0.5010
Topic 9: 0.0873

Topics summary saved to 'topics_summary.csv'.
```

[ ]:

```
```